Agricultural Drone Knowledge Base — India

> **Complete compiled knowledge base on agricultural drones in India** — covering drone hardware and specifications, spare parts, battery databases, crop-wise spraying guidance for 20 major crops, state-wise agricultural profiles, government schemes and subsidies, DGCA regulations, agricultural university research, and drone operator economics. Compiled from **119 source documents across 9 topic areas**.

Keywords: agricultural drone India, drone spraying, DGCA drone rules, drone subsidy, kisan drone, drone sprayer, remote pilot certificate, Digital Sky, precision agriculture, crop protection drone, drone spare parts, drone battery, state-wise agriculture, ICAR drone research, drone operator earnings.

What this document covers

- Agricultural drone hardware: tank capacity, spray width, nozzles, pumps, flight time, battery capacity, coverage per day, water consumption
- Drone spare parts: batteries, chargers, motors, propellers, pumps, nozzles, flow meters, pipes, landing gear, controllers, remote controls, spray tanks
- Drone battery database: type, voltage, capacity, charging time, cycle life, price, compatible drones, manufacturer, maintenance, safety
- Crop-wise spraying for 20 major Indian crops with pest, dosage and timing notes
- State-wise agricultural information for India's states supplied by the source data
- Government schemes and subsidies: central, state, FPO, CHC, women farmer, drone entrepreneur and pilot/operator schemes
- Drone regulations: DGCA, drone categories, pilot certification, registration, Digital Sky, no-fly zones, insurance, spraying requirements
- Agricultural university and ICAR research on drone spraying and field trials
- Drone operator FAQs: cost, earnings per acre, coverage, batteries, maintenance

Known gaps in the source data (reproduced faithfully, not corrected here)

- The state-wise dataset carries **27 states, not 28**: **Tripura is absent**, from both the spreadsheet and the companion document, even though that document is named "28 States".
- `Images.docx` is an image-only document with no extractable text; its 11 figures are preserved in `assets/` rather than as text.
- Three research PDFs appear twice in the source folder under near-identical names (`Drones` / `Drones (1)`, and two others); both copies are included, so section 8 repeats roughly 15% of its content.
- Wide tables in the extracted research papers flatten into running text, so column alignment is not always preserved, though the values are present.

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1. Agricultural Drone Information

agricultural drone specifications, spraying technology, tank and battery capacity, flight time, spray width, nozzle types, water consumption, coverage per day, operating requirements

In this section: Advantages and Limitations, Agricultural drones, Battery Capacity, Charging time, Coverage per day, Drone Capacities, Drone Spraying Technology, Flight TIme, Images, Nozzle types, Operating requirements, Spray width, Tank Capacities, Water Consumption

Advantages and Limitations

Advantages and Limitations

Advantages and limitations of agricultural drones form the dual narrative of modern precision farming and when expanded into a comprehensive synthesis they reveal both the transformative potential and the inherent challenges of UAV spraying systems, advantages begin with water and chemical efficiency, as drones typically consume only 40–120 liters per hectare compared to 200–400 liters in conventional sprayers, representing a 60–70% reduction in water use and a 30–40% reduction in pesticide consumption, which lowers costs, minimizes runoff and protects ecosystems, drones also provide precision targeting, applying chemicals only where needed, reducing overapplication and improving crop health, while labor efficiency is another advantage, since drones replace manual spraying in difficult terrains, reducing human exposure to chemicals and cutting labor costs, speed and accessibility are critical benefits, as drones can cover 10–20 hectares per day depending on payload and battery endurance and they can operate in areas inaccessible to tractors, such as steep slopes, flooded paddies or fragmented smallholder plots, data integration is a further advantage, as drones equipped with multispectral cameras and IoT connectivity can simultaneously monitor crop health, soil moisture and pest incidence, linking spraying with realtime analytics, environmental sustainability is enhanced, since reduced water and chemical use lowers greenhouse gas emissions, protects pollinators and conserves groundwater, economic viability improves as service providers charge per acre based on effective deposition rather than nominal tank size, meaning that efficiency translates directly into profitability, global adoption patterns highlight advantages in diverse contexts, with China deploying rotary atomizer drones across rice fields for massive water savings, Japan using hollowcone nozzles in mountainous paddies for canopy penetration and the US integrating electrostatic nozzles into precision agriculture platforms to minimize drift, however, alongside these advantages are limitations that constrain widespread adoption, beginning with battery endurance, since most drones fly only 15–25 minutes per charge, requiring multiple sorties per hectare and necessitating rapidswap batteries or field charging stations, charging time is another limitation, with standard cycles taking 60–90 minutes unless fast chargers are used, reducing daily coverage, payload capacity is limited, with even large drones carrying only 30–40 liters, far less than tractor sprayers, meaning more flights are needed for large farms, weather dependency is a major limitation, as drones cannot operate in high winds (>15 km/h), heavy rain or extreme heat, since drift, evaporation and turbulence compromise spray quality, regulatory restrictions also limit adoption, with aviation authorities requiring registration, pilot licensing, geofencing and adherence to pesticide laws and compliance costs can be prohibitive for smallholders, operator training is a barrier, since drones require skilled pilots to plan flight paths, calibrate nozzles, monitor battery health and troubleshoot technical issues and certification programs are not universally accessible, maintenance demands are high, with nozzles requiring regular cleaning, pumps needing calibration, firmware requiring updates and batteries needing health monitoring and neglect reduces efficiency and lifespan, safety risks include potential collisions, chemical drift harming neighboring crops or pollinators and battery fires during charging, communication networks are another limitation, as drones require reliable radio or 4G/5G connectivity, which is often lacking in rural areas, data management poses challenges, since drones collect large volumes of multispectral and deposition data that must be stored, processed and analyzed securely and integration with farm management software is not always seamless, environmental adaptability is limited, as drones must withstand dust, humidity and temperature extremes and ruggedized casings increase costs, economic barriers persist, since drones are expensive to purchase and maintain and while service models reduce upfront costs, affordability remains a challenge for smallholders,

globally, limitations manifest differently, with China overcoming endurance issues through rapid battery swapping, Japan facing weather constraints in mountainous terrain and the US grappling with regulatory compliance and data integration, future innovations aim to overcome limitations, including hydrogen fuel cell drones that eliminate charging downtime, AI autopilot systems that adjust flight parameters in real time, modular drones that switch payloads midflight, swarm UAV networks that rotate between spraying and charging to ensure uninterrupted coverage and blockchainbased compliance systems that automatically log pesticide use for regulatory authorities, in conclusion, advantages and limitations together define the trajectory of agricultural drones and at approximately underscores that while drones offer water efficiency, precision targeting, labor savings, speed, data integration, sustainability and profitability, they are constrained by endurance, charging, payload, weather, regulation, training, maintenance, safety, connectivity, data management, adaptability and cost, proving that drones are both the promise and the challenge of precision agriculture, where every advantage must be balanced against a limitation and every limitation must be addressed by innovation, ensuring that UAV spraying evolves from experimental technology into a cornerstone of global food security, climate resilience and sustainable farming.

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Agricultural drones

Agricultural Drones

Agricultural drones, also known as UAVs (Unmanned Aerial Vehicles), have emerged as one of the most transformative technologies in modern farming, enabling precision agriculture practices that optimize resources, reduce costs and improve yields. These drones are equipped with GPS, cameras, multispectral sensors and spraying mechanisms, allowing farmers to monitor crop health, map fields and apply pesticides or fertilizers with remarkable accuracy. By flying over fields, drones capture highresolution images that reveal variations in plant growth, soil conditions and water stress, helping farmers make datadriven decisions. For instance, drones can detect early signs of disease or nutrient deficiency, enabling timely interventions that prevent largescale crop loss. In spraying applications, drones atomize chemicals into fine droplets, ensuring uniform coverage while reducing pesticide use by up to 40% and saving nearly 70% water compared to traditional methods. This not only lowers input costs but also minimizes environmental damage from chemical runoff.

The benefits of agricultural drones extend beyond efficiency. They empower smallholder farmers by reducing dependence on manual labor, as one operator can cover several hectares in a short time. They also enhance sustainability by cutting carbon emissions associated with tractorbased spraying. In countries like India, where fragmented landholdings and labor shortages are common, drones offer scalable solutions for both small and large farms. However, challenges remain: high initial costs make adoption difficult for marginal farmers, battery limitations restrict flight duration and regulatory hurdles vary across regions, requiring licenses and permissions for drone operations. Moreover, farmers need training to operate drones and interpret the complex data they generate. Weather conditions also play a critical role, as strong winds or rain can disrupt drone flights and affect accuracy.

Looking ahead, the future of agricultural drones is promising. Integration with AI and machine learning will enable predictive analytics, allowing drones to forecast yields, recommend precise fertilizer application and even autonomously manage entire fields. Governments are increasingly supporting drone adoption through subsidies and pilot programs, especially in India, where initiatives under the PMKisan scheme and startups like Garuda Aerospace are driving awareness and accessibility. As climate change intensifies, drones will become vital tools in climatesmart agriculture, helping farmers adapt by monitoring crop resilience, optimizing irrigation and reducing resource wastage. With continuous innovation, drones are poised to become mainstream farming equipment, bridging the gap between traditional practices and digital agriculture.

But to truly understand their impact, we must go deeper into the economics, sustainability and social dimensions. Research shows drones save 70–90% water compared to knapsack sprayers, a critical advantage in droughtprone regions. They reduce pesticide drift by up to 80%, protecting neighboring crops and communities. Life Cycle Assessments in India found drones cut CO_2 emissions by 50% compared to tractor

spraying, thanks to lower fuel use and reduced chemical inputs. Economic analysis reveals farmers recover drone investment within 2–3 crop seasons, especially when using service models at ₹500–700 per acre.

Beyond numbers, drones reshape farmer livelihoods. Manual spraying often exposes farmers to toxic chemicals, leading to respiratory issues and skin irritation. Drones keep farmers at a safe distance, reducing health risks and medical expenses. They also reduce labor dependence, a major issue in regions facing ruralurban migration. Instead of hiring multiple workers, one trained operator can manage spraying across dozens of acres. This efficiency not only saves costs but also ensures timely pest control, preventing yield losses.

Community adoption models are emerging as powerful drivers. Cooperatives and Farmer Producer Organizations (FPOs) pool resources to buy drones collectively, spreading costs and benefits across members. Rural youth are being trained as drone pilots, creating new employment opportunities and reducing migration to cities. Service providers are building businesses around drone spraying, offering affordable solutions to smallholders who cannot buy drones outright. These models democratize access and accelerate adoption.

Policy support is another critical factor. The Indian government has introduced subsidies covering 40–50% of drone costs, along with training programs under the PMKisan scheme. Initiatives like Namo Drone Didi empower women farmers by providing drones and training, promoting gender inclusion in agritech. Regulatory frameworks are evolving to streamline licensing and permissions, making drone operations easier for farmers.

Climate resilience is perhaps the most overlooked benefit. As weather patterns become unpredictable, timely spraying is essential. Manual spraying is slow and tractors cannot enter flooded fields. Drones, however, can operate in waterlogged paddy or after sudden pest outbreaks, ensuring crops are protected even under adverse conditions. This resilience reduces yield losses and stabilizes farmer income in the face of climate change.

The integration of AI and IoT will take drones to the next level. Multispectral sensors already detect crop stress but future drones will use machine learning to recommend precise interventions. Variablerate spraying will apply different doses based on crop health, further reducing costs and improving yields. Drones will also integrate with satellite data, weather forecasts and soil sensors, creating a holistic digital farming ecosystem.

Globally, adoption is accelerating. In China, millions of hectares are already managed with drones. In Japan, drones are used for rice spraying in mountainous regions where tractors cannot operate. In the US, drones are integrated with precision agriculture platforms, combining aerial imagery with yield maps and soil data. India is catching up fast, with startups like Garuda Aerospace, IoTechWorld and General Aeronautics leading the charge.

High initial costs deter marginal farmers, though service models and subsidies are addressing this. Battery limitations restrict flight duration, requiring multiple charges for large fields. Weather conditions like strong winds or rain can disrupt spraying. Farmers need training not only to operate drones but also to interpret the complex data they generate. Yet these challenges are surmountable and innovation is rapidly solving them. Agricultural drones are not just gadgets, they are engines of profit, sustainability and resilience. By saving water, reducing chemical use, cutting labor and fuel costs, improving yields and lowering hidden expenses, drones deliver more crop per rupee spent. They protect farmer health, build climate resilience and create new rural livelihoods. For farmers seeking to maximize profits and minimize risks, drones are the smarter, safer and more sustainable investment.

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Battery Capacity

Battery Capacity

Battery capacity in agricultural drones is one of the most decisive engineering parameters that governs endurance, payload efficiency and overall suitability for precision farming and unlike simple consumer UAVs, spraying drones require batteries that can sustain heavy payloads, atomization systems and long sorties under variable field conditions, with research consistently showing that lithiumpolymer (LiPo) and lithiumion (Liion)

chemistries dominate because of their high energy density and discharge rates, yet even within these categories capacity varies widely, typically ranging from 8,000 mAh in small 10liter drones to 30,000–40,000 mAh in large 40liter spraying drones, translating into energy ratings of 200–1,200 Wh depending on design; the principle behind battery capacity is rooted in energy balance, where stored electrical energy must match the thrust required to lift payloads, power atomizers and maintain stable flight and the heavier the payload the greater the current draw, which shortens endurance, meaning that drones with larger tanks often sacrifice flight duration compared to smaller models, while nozzle atomization systems also influence efficiency since droplet size and spray pressure affect motor load and airflow dynamics, with rotary atomizers producing uniform droplets but increasing current demand; studies in China and India confirm that a 16liter drone equipped with a 22,000 mAh LiPo battery achieves 18–25 minutes of flight time, covering 1–2 hectares per sortie, while a 30liter drone with a 30,000 mAh battery sustains 15–20 minutes, covering 5–8 hectares and highend 40liter drones using dual 40,000 mAh packs can cover up to 15 hectares per hour but only with multiple batteries and rapid swapping systems to maintain continuous operation; endurance is further influenced by environmental conditions—wind increases drag and power consumption, high temperatures reduce battery efficiency and terrain complexity such as hilly or orchard landscapes demands more maneuvering and energy, while cold weather reduces discharge efficiency and shortens usable capacity; global research emphasizes that battery degradation is a critical factor, with LiPo batteries losing 15–20% capacity after 200–300 cycles, necessitating replacement and increasing operational costs and comparative trials highlight that endurance drops by 20–30% when payloads exceed optimal ratios, underscoring the importance of balancing tank size with battery capacity; innovations are emerging to address these limitations, including hybrid power systems that combine LiPo batteries with hydrogen fuel cells to extend endurance beyond one hour, solarassisted charging integrated into wings or fuselage to supplement energy midflight, AIdriven flight optimization that minimizes unnecessary maneuvers and reduces current draw and lightweight composite materials that reduce structural weight without compromising durability, with prototypes already demonstrating endurance beyond 60 minutes in controlled environments; beyond spraying, battery capacity also governs imaging payloads, as multispectral cameras, LiDAR sensors and thermal imagers add weight and increase energy demand, requiring careful balance between sensor utility and endurance; economic implications are significant, since larger batteries cost ₹8,000–25,000 each and require multiple units for continuous operation, while smaller batteries are cheaper but limit throughput and service providers often deploy midcapacity drones with 20,000–25,000 mAh batteries for smallholder farms, charging ₹500–700 per acre, which balances efficiency and affordability; globally, adoption patterns vary, with China deploying large drones powered by 30,000–40,000 mAh packs across millions of hectares, Japan favoring smaller drones with 10,000–15,000 mAh batteries for mountainous rice fields and the US integrating midcapacity drones into precision agriculture platforms, combining aerial imagery with yield maps and soil data; environmental benefits of optimized battery capacity are substantial, as reduced chemical runoff protects soil and water bodies, lower fuel use cuts greenhouse gas emissions and UAV spraying in orchards has been shown to lower energy consumption by 67% compared to tractor sprayers, while batterypowered drones eliminate diesel emissions entirely; future research is focusing on solidstate batteries with higher energy density and safety, modular battery packs that allow hotswapping without interrupting flights and smart battery management systems that monitor discharge rates, temperature and cycle health in real time, enabling predictive maintenance and longer service life; despite these advances, challenges remain, short flight times necessitate multiple batteries, increasing operational costs, battery degradation reduces capacity over time and regulatory restrictions often limit maximum flight duration for safety reasons but continuous research points toward scalable solutions that will enhance battery capacity without compromising payload efficiency, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and as battery technology evolves, drones will not only spray pesticides but also carry advanced sensors for monitoring, mapping and predictive analytics, making battery capacity optimization the cornerstone of their evolution into multifunctional platforms that integrate spraying, imaging and autonomous decisionmaking into a single aerial system, thereby redefining the economics and sustainability of modern agriculture and ensuring that every milliampere of stored energy translates into measurable gains in productivity, profitability and environmental stewardship.

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Charging time

Charging Time

Charging time in agricultural drones is one of the most decisive operational parameters because it directly governs how efficiently spraying schedules can be maintained, how many hectares can be covered in a day and how economically viable drone services are for farmers and unlike payload or spray width which define coverage, charging time defines downtime, with most current UAVs powered by lithiumion or lithiumpolymer batteries requiring 30–90 minutes for a full charge depending on capacity, chemistry and charger technology, though rapidswap battery systems and fastcharging innovations are reducing this to under 15–20 minutes per cycle, battery chemistry plays a central role, with lithiumion batteries offering stability but longer charging cycles (60–90 minutes), lithiumpolymer batteries allowing faster charging (~30–60 minutes) but degrading quicker and emerging solidstate batteries promising <30 minutes charging with higher energy density and longer lifespans; charger technology is equally critical, as standard chargers deliver 1C–2C rates (1–2 hours), fast chargers (3C–5C) reduce charging time to 20–40 minutes and wireless charging pads or bidirectional charging stations are being tested in smart agriculture networks to enable continuous UAV operation without manual intervention; battery capacity scales charging time, with small drones (10–16 L tanks) using 6–8 Ah batteries charging in ~30 minutes, midcapacity drones (20–25 L tanks) using 12–16 Ah batteries charging in ~60 minutes and large drones (30–40 L tanks) using 20–30 Ah batteries requiring 90+ minutes unless fast chargers are used; endurance constraints interact with charging time, since larger batteries extend flight duration but increase downtime per charge, while smaller batteries reduce downtime but demand more frequent swaps, making charging optimization a balance between flight endurance and turnaround speed; research highlights reinforcementlearning charging strategies that reduce UAV downtime by 40% in multidrone agricultural networks, pathplanning integration that allows drones to autonomously fly to charging stations and wireless bidirectional charging trials in smart agriculture networks that show potential for uninterrupted UAV operation; challenges remain, including heat buildup during fast charging which reduces battery lifespan, infrastructure costs for multiple charging stations in rural areas, battery degradation accelerated by repeated rapid charging cycles and regulatory limits on charging station placement; future directions include hybrid drones combining batteries with hydrogen fuel cells for nearinstant refueling, solar charging stations deployed in fields to reduce downtime, AIdriven charging optimization predicting optimal cycles to balance speed and battery health and swarm UAV networks where drones rotate between charging and spraying to ensure uninterrupted coverage; economic implications are significant, since faster charging reduces downtime and increases daily coverage, lowering service costs per hectare, while environmental benefits include reduced reliance on fossil fuelbased spraying equipment and lower greenhouse gas emissions; globally, adoption patterns vary, with China deploying rapidswap battery systems for rice spraying, Japan experimenting with solar charging stations in mountainous paddies and the US integrating wireless charging pads into precision agriculture platforms; in conclusion, charging time is not a minor technical detail but a cornerstone of drone spraying efficiency and at approximately 5000 words of elaboration this synthesis underscores that optimizing charging time through battery chemistry, charger technology and operational strategies is central to climatesmart agriculture, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, resilience and sustainability, proving that every minute saved in charging is an acre gained in spraying and that charging time optimization is the defining feature of UAV spraying systems in the decades ahead.

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Coverage per day

Coverage per day

Coverage per day in agricultural drone operations refers to the total area a UAV can effectively spray, monitor or map within a 24hour cycle and it is one of the most decisive indicators of operational efficiency, cost effectiveness and suitability for different farming scales, with research showing that daily coverage is

determined by a complex interplay of payload capacity, battery endurance, refilling logistics, terrain accessibility, weather conditions and operator skill, rather than just tank size or flight time alone; modern spraying drones with 10–16 liter tanks typically cover 20–30 acres per day under fragmented landholding conditions, while midcapacity drones with 20–25 liter tanks can achieve 40–60 acres per day and large drones with 30–40 liter tanks, when operated with multiple batteries and rapid refilling systems, can reach 80–120 acres per day, though these figures vary significantly depending on crop type, canopy density and terrain complexity, as flat fields allow maximum throughput while orchards or hilly landscapes reduce efficiency due to maneuvering demands; endurance constraints are critical, since most drones operate for 15–30 minutes per charge, requiring 6–10 sorties and multiple battery swaps to sustain daily operations and research emphasizes that nozzle atomization efficiency directly influences coverage because droplet size and spray uniformity determine how much chemical is effectively deposited per hectare, with rotary atomizers improving deposition but increasing current draw, thereby reducing sortie duration; comparative trials in China, Japan and India highlight that daily coverage drops by 20–30% under windy or hot conditions due to increased drag and reduced battery efficiency, while cold weather shortens discharge capacity and terrain fragmentation further reduces throughput because drones spend more time repositioning between plots; operational logistics also play a decisive role, as refilling stations, battery charging hubs and trained operators determine how many sorties can be sustained in a day, with studies showing that efficient logistics can increase daily coverage by 25–40% compared to ad hoc operations; economic analysis reveals that service providers typically charge ₹500–700 per acre, meaning that a drone covering 60 acres per day generates ₹30,000–40,000 in gross service value, making daily coverage a direct driver of profitability, while larger drones with higher throughput reduce peracre costs but increase capital investment and regulatory complexity; future innovations aim to extend daily coverage through hybrid power systems that combine batteries with fuel cells for longer endurance, solarassisted charging stations that reduce downtime, AIdriven flight optimization that minimizes unnecessary maneuvers and modular payload systems that allow rapid switching between tanks and sensors, thereby reducing turnaround time; globally, adoption patterns vary, with China deploying fleets of large drones covering hundreds of acres per day across collective farms, Japan favoring smaller drones for mountainous rice fields with daily coverage of 10–15 acres and the US integrating midcapacity drones into precision agriculture platforms where daily coverage is optimized through coordinated fleet operations; environmental benefits of optimized daily coverage are substantial, as reduced chemical runoff protects soil and water bodies, lower fuel use cuts greenhouse gas emissions and UAV spraying in orchards has been shown to lower energy consumption by 67% compared to tractor sprayers, while higher daily coverage ensures timely pest control, reducing yield losses and stabilizing farmer income; despite these advances, challenges remain, short flight times necessitate multiple batteries, increasing operational costs, nozzle design must balance droplet uniformity with energy efficiency and regulatory restrictions often limit maximum sortie numbers for safety reasons but continuous research points toward scalable solutions that will enhance daily coverage without compromising payload efficiency, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and as coverage per day improves, drones will not only spray pesticides but also carry advanced sensors for monitoring, mapping and predictive analytics, making daily coverage optimization the cornerstone of their evolution into multifunctional platforms that integrate spraying, imaging and autonomous decisionmaking into a single aerial system, thereby redefining the economics and sustainability of modern agriculture and ensuring that every hectare covered translates into measurable gains in productivity, profitability and environmental sustainability.

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Drone Capacities

Drone Capacities

Drone capacity in agriculture is not a simple metric of how much liquid a UAV can carry; it is a complex interplay of payload volume, battery endurance, nozzle atomization efficiency, flight stability and operational throughput. Together, these factors determine how effectively drones can perform spraying, monitoring and

mapping tasks across diverse farming systems. Modern agricultural drones are designed to carry payloads ranging from 10 liters for smallholder farms to 40 liters for commercial operations, with coverage capacities of 1–2 hectares per flight for smaller drones and up to 15 hectares per hour for larger ones under ideal conditions. Yet this payloadtoendurance ratio is a delicate balance: increasing tank size reduces flight time due to added weight, making battery endurance, typically 15–30 minutes per charge, a critical limiting factor that requires multiple batteries or fastcharging systems for continuous use.

The atomization process is central to drone spraying capacity. Rotary atomizers spin at high speeds, breaking liquid into uniform droplets, while hydraulic nozzles use pressure to create fine sprays. Research shows droplet sizes of 200–300 microns are optimal for minimizing drift and maximizing canopy penetration. The downward rotor airflow enhances deposition in dense foliage, ensuring pesticides reach hidden pests such as stem borers in rice or bollworms in cotton. Compared to conventional sprayers, drones improve pesticide efficiency by 30–40%, reducing chemical use and environmental contamination.

Battery endurance remains the most significant constraint. A 10liter drone may fly for 25–30 minutes, covering 1–2 hectares, while a 40liter drone may fly only 15–20 minutes, covering larger areas but requiring frequent recharges. Payloadtoendurance ratios are critical: heavier tanks reduce flight stability and drain batteries faster. Research emphasizes modular battery systems and rapid charging stations as solutions, enabling continuous spraying cycles. Hybrid power systems combining batteries with fuel cells are being tested to extend endurance beyond one hour, potentially revolutionizing drone capacity. Larger drones, while capable of higher throughput, face stricter licensing requirements and demand skilled operators. Service providers often prefer midcapacity drones for smallholder farms, charging ₹500–700 per acre, which is costeffective compared to manual labor and tractor spraying.

Drone capacity also extends beyond spraying to imaging payloads. Multispectral cameras, LiDAR sensors and thermal imagers add weight but enable advanced applications like yield prediction, soil variability mapping and irrigation management. Payload design must balance weight distribution to maintain flight stability. Modular payload platforms are emerging, allowing farmers to switch between spraying tanks and sensors depending on need. This flexibility enhances drone utility across multiple agricultural tasks.

Nozzle efficiency is another determinant of capacity. Atomization principles directly affect drift, deposition and chemical efficiency. Rotary atomizers produce more uniform droplets, reducing drift by up to 80%. Intelligent nozzle systems integrated with AI can adjust droplet size and spray rate based on crop density and canopy structure, further optimizing efficiency.

Operational throughput depends on terrain and crop type. In flat fields, drones achieve maximum coverage, while in orchards or hilly regions, coverage is reduced due to navigation complexity. Flight stability is critical in windy conditions, as turbulence affects droplet deposition. Advanced drones use gyroscopic stabilization and realtime sensors to maintain accuracy even under challenging weather. Economic implications of drone capacity are significant. Larger payload drones reduce spraying time but increase costs and regulatory complexity. Smaller drones are cheaper and easier to operate but require more flights to cover large areas. Farmers must balance investment with operational needs. Cooperatives and Farmer Producer Organizations (FPOs) often pool resources to purchase midcapacity drones, spreading costs and benefits across members. Rural youth are trained as drone pilots, creating new employment opportunities and reducing migration to cities.

Environmental benefits of optimized drone capacity are substantial. Reduced chemical runoff protects soil and water bodies, preserving fertility and biodiversity. Lower fuel use cuts greenhouse gas emissions. Life Cycle Assessments in India found drones reduce CO_2 emissions by 50% compared to tractor spraying. In orchards, UAV spraying lowered energy consumption by 67% compared to conventional methods. These savings make drones central to climatesmart agriculture.

Hybrid drones combining battery and fuel cells could extend endurance beyond one hour. Modular payloads will allow farmers to switch between spraying tanks, cameras and sensors depending on need. AI will enable drones to autonomously adjust spray rates and coverage based on realtime crop health data, further improving efficiency. Integration with IoT devices—soil sensors, weather stations, satellite data—will create a holistic digital farming ecosystem.

Globally, adoption is accelerating. In China, drones with 30–40 liter tanks manage thousands of hectares. In Japan, smaller drones are used in mountainous rice fields. In the US, drones integrate with precision agriculture platforms, combining aerial imagery with yield maps and soil data.

Drone capacity is not just a technical specification, it is the foundation of precision agriculture. By balancing payload, endurance, nozzle efficiency and operational throughput, drones deliver more crop per rupee spent, protect farmer health and reduce environmental impact. They are not merely tools of convenience but essential instruments in the sustainable transformation of global food production.

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Drone Spraying Technology

"Drone Spraying Technology"

Drone spraying technology operates on the principle of atomization, where liquid agrochemicals such as pesticides, herbicides or fertilizers are broken down into fine droplets through specialized nozzles or rotary atomizers mounted on unmanned aerial vehicles (UAVs). These droplets, typically in the range of 200–300 microns, are dispersed uniformly across crop canopies by the downward airflow generated by the drone's rotors, ensuring precise coverage while minimizing drift and wastage. The system integrates GPSguided navigation and realtime sensors to maintain consistent flight paths and spray volumes, allowing drones to adjust droplet size and application rate based on crop density, canopy structure and environmental conditions. This makes them far more efficient than conventional tractor sprayers that often waste chemicals and water due to uneven distribution.

In practice, drone spraying reduces pesticide use by 30–40%, saves up to 70% water and lowers chemical runoff that contaminates soil and water bodies, while also cutting carbon emissions by nearly 50% since drones replace fuelintensive machinery. Beyond efficiency, this technology enhances farmer safety by reducing direct exposure to toxic chemicals, accelerates spraying in large or fragmented fields and provides accessibility in terrains where tractors cannot operate, such as orchards, hilly regions or small plots.

The atomization process itself is a marvel of engineering. Rotary atomizers spin at high speeds, breaking liquid into uniform droplets. Hydraulic nozzles, meanwhile, use pressure to create fine sprays. The downward thrust of drone rotors pushes these droplets into the crop canopy, ensuring penetration even in dense foliage. Unlike manual spraying, where droplets often drift away or fail to reach lower leaves, drones achieve consistent deposition. This precision is critical in controlling pests like stem borers in rice or bollworms in cotton, which hide deep within plant structures.

GPS and sensor integration elevate drones from simple sprayers to intelligent machines. Flight paths are preprogrammed, ensuring uniform coverage without overlap or gaps. Sensors monitor wind speed, humidity and crop density, adjusting spray volume accordingly. Some advanced drones even use multispectral cameras to detect crop stress, allowing variablerate spraying, more pesticide where pests are dense, less where crops are healthy. This reduces costs and environmental impact simultaneously.

Economically, drones are reshaping farm budgets. Manual spraying requires multiple laborers, each covering only 2–3 acres per day. Tractor spraying is faster but consumes diesel, requires maintenance and damages soil through compaction. Drones, by contrast, cover 30–50 acres per day with one operator, using minimal water and chemicals. Service providers charge ₹500–700 per acre, which is often cheaper than hiring labor and buying excess pesticides. Farmers report yield gains of 10–15% due to uniform spraying, meaning drones not only cut costs but also increase income.

Environmental benefits are equally striking. Reduced chemical runoff protects soil and water bodies, preserving fertility and biodiversity. Lower fuel use cuts greenhouse gas emissions. Studies in India and China show drones reduce CO_2 emissions by 50% compared to tractor spraying. In orchards, UAV spraying lowered energy consumption by 67% compared to conventional methods. These savings make drones central to climatesmart agriculture.

Farmer safety is another dimension. Manual spraying exposes farmers to toxic chemicals, leading to respiratory issues, skin irritation and longterm health problems. Drones keep farmers at a safe distance,

reducing exposure and medical expenses. This is particularly important in crops like chilli, where thrips control requires frequent spraying or cotton, where bollworm infestations demand repeated pesticide applications. Tractors cannot enter waterlogged paddy fields or steep orchards. Manual spraying in such terrains is slow and dangerous. Drones fly over these obstacles, delivering sprays quickly and safely. In fragmented landholdings, common in India, drones navigate small plots efficiently, something tractors struggle with.

Subsidies cover 40–50% of costs, service models spread expenses and startups provide affordable spraying services. Battery technology is improving, with longer flight times and faster charging. Regulations are evolving to streamline permissions. AI and machine learning integration will enable predictive spraying, yield forecasting and autonomous field management. Drones will analyze crop health in real time, recommend interventions and even execute them autonomously. Integration with IoT devices—soil sensors, weather stations, satellite data, will create a holistic digital farming ecosystem. Governments are supporting adoption through subsidies and pilot programs. Startups like Garuda Aerospace and IoTechWorld Avigation are offering drone spraying services at affordable rates, making the technology more accessible.

Globally, adoption is accelerating. In China, millions of hectares are managed with drones. In Japan, drones spray rice in mountainous regions where tractors cannot operate. In the US, drones integrate with precision agriculture platforms, combining aerial imagery with yield maps and soil data. India is catching up fast, with startups and government initiatives driving awareness and accessibility.

As climate change intensifies, drone spraying will play a critical role in climatesmart agriculture. By optimizing resource use, reducing environmental impact and enhancing crop resilience, drones bridge the gap between traditional farming and digital agriculture. They are not just tools of convenience but essential instruments in the sustainable transformation of global food production.

Source: `Drone Spraying Technology.docx` · Google Drive file id `1CByGBPaIVrQ3gYfs499Q5WDzZngp9MQq` · folder “1. Agricultural Drone Information”

Flight TIme

Flight Time

Flight time of agricultural drones is one of the most decisive parameters that governs their efficiency, coverage and suitability for different farming operations and it is fundamentally determined by the interplay between battery capacity, payload weight, motor efficiency and aerodynamic design, with most spraying drones today offering endurance between 15–40 minutes per charge, which translates to coverage of 1–15 hectares depending on tank size and terrain; the principle behind flight time is rooted in energy balance, where lithiumpolymer or lithiumion batteries supply electrical energy to brushless motors and the heavier the payload (spray tank, sensors or cameras), the greater the thrust required, which in turn increases current draw and reduces endurance, meaning that drones with larger tanks (20–40 liters) often sacrifice flight duration compared to smaller 10–16 liter models, while nozzle atomization systems also influence efficiency since droplet size and spray pressure affect motor load and airflow dynamics, with rotary atomizers producing uniform droplets but increasing current demand; research shows that a 16liter drone typically achieves 18–25 minutes of flight time, covering 1–2 hectares per sortie, whereas a 30liter drone may only sustain 15–20 minutes, covering 5–8 hectares per sortie and highend 40liter drones can cover up to 15 hectares per hour but require multiple batteries and rapid swapping systems to maintain continuous operation; endurance is further influenced by environmental conditions, wind increases drag and power consumption, high temperatures reduce battery efficiency and terrain complexity such as hilly or orchard landscapes demands more maneuvering and energy; global studies emphasize that endurance evaluation models now modularly divide UAV power output and battery discharge rates to predict flight time under different payloads, while comparative trials in Asia and Europe confirm that endurance drops by 20–30% when payloads exceed optimal ratios, highlighting the importance of balancing tank size with battery capacity; future innovations aim to extend flight time through hybrid power systems that combine batteries with hydrogen fuel cells, solarassisted charging integrated into wings or fuselage, AIdriven flight optimization that minimizes unnecessary maneuvers and lightweight composite materials that reduce structural weight without compromising durability, with prototypes already demonstrating endurance beyond one hour in controlled environments;

despite these advances, challenges remain, short flight times necessitate multiple batteries, increasing operational costs, nozzle design must balance droplet uniformity with energy efficiency and regulatory restrictions often limit maximum flight duration for safety reasons but continuous research points toward scalable solutions that will enhance flight time without compromising payload capacity, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and as endurance improves, drones will not only spray pesticides but also carry multispectral sensors, LiDAR payloads and thermal imagers for advanced monitoring, making flight time optimization the cornerstone of their evolution into multifunctional platforms that integrate spraying, imaging and predictive analytics into a single aerial system, thereby redefining the economics and sustainability of modern agriculture.

Source: `Flight TIme.docx` · Google Drive file id `1LNeh0j_M4q_qyeRGjWBKBx08ZVNgs1C7` · folder “1. Agricultural Drone Information”

Images

This entry is an image-only document. The embedded figures are preserved in the knowledge-base asset bundle.

Specifications:

- Capacity: 1800mAh
- Voltage: 14.8V / 4S / 4 Cell
- Discharge Rate: 75C
- Max Burst Discharge Rate: 150C
- Weight: 202g
- Size: 106mm x 36mm x 25mm (L x W x H)
- Connector Type: XT-60

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Nozzle types

Nozzle Types

Nozzle types in agricultural drones are arguably the most decisive engineering components that govern spray quality, droplet size distribution, drift potential, canopy penetration and overall efficiency of pesticide, herbicide and foliar nutrient applications and unlike payload or battery capacity, nozzle geometry directly controls how chemicals are atomized, dispersed and deposited across crop canopies, making nozzle selection central to precision agriculture and environmental sustainability; research across multiple peerreviewed studies confirms that nozzle choice determines spray angle, swath width, deposition uniformity and chemical efficiency, with five major categories dominating drone spraying systems: flatfan nozzles, hollowcone nozzles, airinduction nozzles, rotary atomizers and electrostatic nozzles, each with distinct advantages and limitations; flatfan nozzles are widely used for broad acre crops like rice and wheat, producing mediumsized droplets (250–350 μm) in a fanshaped spray pattern that ensures uniform coverage but increases drift risk under windy conditions; hollowcone nozzles generate fine droplets (<200 μm) with circular spray patterns, offering superior canopy penetration in dense crops such as cotton, maize or orchards but their fine droplets are highly driftprone, requiring careful calibration of flight height and rotor speed; airinduction nozzles mix liquid with air to produce larger, airfilled droplets (400–600 μm) that reduce drift by up to 60% while maintaining adequate coverage, making them ideal for vineyards and orchards where offtarget contamination is a concern; rotary atomizers use spinning discs or cages to break liquid into uniform droplets, achieving highly consistent deposition and adjustable droplet sizes, with studies confirming 30–40% chemical savings compared to hydraulic nozzles, though they demand higher motor power and increase current draw, thereby shortening endurance; electrostatic nozzles charge droplets electrically, enhancing adhesion to leaf surfaces and reducing runoff by over 60%, with trials in rice fields showing 41% water savings and 43% pesticide reduction, alongside significant greenhouse gas emission cuts due to lower pump energy use and comparative assessments highlight that nozzle type interacts strongly with flight height and rotor downwash, with flatfan nozzles performing best at 3 m, hollowcone at 2.5 m and rotary atomizers at 2–3 m, while canopy coverage and droplet density vary significantly across altitudes; research also emphasizes drift potential scaling, showing that nozzle geometry, droplet size and spray angle collectively determine airborne drift, with hollowcone nozzles having the highest drift potential and airinduction the lowest and global adoption patterns reflect these tradeoffs: in China, rotary atomizers dominate largescale rice spraying due to their efficiency; in Japan, hollowcone nozzles are favored for mountainous rice paddies where canopy penetration is critical; in the US, airinduction and electrostatic nozzles are integrated into precision agriculture platforms to minimize drift and maximize deposition; environmental benefits of optimized nozzle use are substantial, as reduced chemical runoff protects aquatic ecosystems, lower water use conserves resources and minimized drift reduces exposure risks for neighboring communities, while economic implications are equally significant, since nozzle choice directly affects input costs, with finer droplets reducing pesticide volumes but increasing drift risk and larger droplets reducing drift but potentially compromising coverage, requiring farmers and service providers to calibrate nozzle type to crop, terrain and weather; future innovations include smart nozzles with AIdriven droplet control, modular nozzle arrays that switch types midflight and integrated sensors that monitor deposition in real time, enabling drones to autonomously adjust spray parameters for maximum efficiency and beyond spraying, nozzle types also govern foliar nutrient application and biological control agent delivery, where uniform coverage is essential for efficacy, with imaging payloads such as multispectral cameras integrated to monitor deposition patterns in real time, enabling corrective adjustments midflight; despite these advances, challenges remain—nozzle clogging reduces effective swath, spray width is highly sensitive to weather conditions and regulatory frameworks often limit maximum spray angles for safety reasons but continuous research points toward scalable solutions that will enhance nozzle performance without compromising deposition uniformity, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and at approximately 5000 words of elaboration, this comprehensive synthesis underscores that nozzle optimization is not a minor technical detail but the cornerstone of drone spraying systems, ensuring that every droplet released is not just a chemical particle but a carefully engineered unit of productivity, profitability and environmental stewardship, redefining the economics and sustainability of modern agriculture and proving that nozzle types are the true precision instruments of aerial farming.

Operating requirements

Operating requirements

Operating requirements in agricultural drones are an expansive framework that integrates technical specifications, environmental thresholds, regulatory mandates, safety protocols and socioeconomic feasibility and when fully elaborated they reveal the complexity of deploying UAV spraying systems in real farming contexts, battery endurance is a fundamental requirement, with most drones offering 15–25 minutes of flight per charge depending on payload, necessitating multiple sorties per hectare and requiring rapidswap battery systems or field charging stations to maintain operational continuity, charging infrastructure is equally critical, since standard chargers take 60–90 minutes while fast chargers and solarassisted stations reduce downtime to 20–40 minutes, ensuring higher daily coverage, payload capacity defines operational limits, with small drones carrying 10–16 liters, midrange drones 20–25 liters and large drones 30–40 liters and payload must be balanced against endurance to avoid overloading and premature power loss, nozzle calibration is another requirement, as droplet size, spray angle and deposition uniformity must be optimized for each crop, with flatfan nozzles suited for broad acre crops, hollowcone for dense canopies, rotary atomizers for uniform deposition and electrostatic nozzles for water savings and adhesion and improper calibration leads to drift, wastage and regulatory violations, flight altitude and speed are tightly regulated, with drones required to fly at 2–3 meters above canopy at speeds of 3–5 m/s to ensure uniform coverage and deviations can cause uneven deposition or excessive drift, weather conditions form a nonnegotiable requirement, as drones cannot operate in high winds (>15 km/h), heavy rain or extreme heat, since drift, evaporation and turbulence compromise spray quality and guidelines mandate strict adherence to meteorological thresholds, regulatory compliance is a core requirement, with aviation authorities requiring drone registration, pilot licensing, geofencing and adherence to pesticide application laws and failure to comply can result in penalties or bans, operator training is essential, as drones require skilled pilots to plan flight paths, calibrate nozzles, monitor battery health and troubleshoot technical issues and certification programs are mandated to ensure safety and efficiency, integration with digital agriculture platforms is increasingly part of operating requirements, as drones are expected to link with GIS maps, IoT soil sensors and AIdriven decision support systems to optimize spraying schedules, water use and chemical application, ensuring drones are part of a precision farming ecosystem, maintenance protocols are mandatory, including regular cleaning of nozzles, calibration of pumps, firmware updates and battery health monitoring and neglecting these reduces efficiency and lifespan, safety systems are required, such as obstacle detection sensors, emergency landing protocols and failsafe returntohome features, which protect both operators and crops, communication networks form another requirement, as drones must operate within reliable radio frequencies or 4G/5G connectivity to ensure uninterrupted control, especially in large farms and weak connectivity can cause mission failure, data management is increasingly recognized, since drones collect multispectral and deposition data that must be stored, processed and analyzed securely and integration with farm management software is essential, environmental adaptability is vital, as drones must withstand dust, humidity and temperature extremes, with ruggedized casings and waterproofing becoming standard, redundancy planning requires backup drones, spare batteries and duplicate nozzles to ensure uninterrupted spraying in case of technical failure, logistical support involves transport vehicles, ground crews and storage facilities to move drones between fields efficiently, chemical compatibility ensures drones can handle a wide range of pesticides, herbicides and foliar nutrients without corroding tanks or clogging nozzles, ergonomic design ensures operators can easily swap batteries, refill tanks and calibrate nozzles without excessive strain, socioeconomic feasibility balances affordability for smallholders with scalability for agribusiness, making operating requirements a matter of equity as well as efficiency, globally, operating requirements vary, economic implications are significant, since meeting operating requirements increases upfront costs for infrastructure and training but reduces longterm costs through efficiency gains, while environmental benefits include reduced chemical runoff, lower water use and minimized drift, future innovations include AIdriven autopilot systems that adjust flight parameters in real time, modular drones that switch payloads midflight, hydrogen fuel cell drones that eliminate charging downtime, swarm UAV networks that rotate between spraying and charging to ensure uninterrupted coverage and block chainbased compliance systems that automatically log pesticide use for regulatory authorities, in conclusion, operating requirements are not peripheral considerations but the foundation of drone spraying systems and at approximately

underscores that battery endurance, charging infrastructure, payload calibration, flight altitude, weather thresholds, regulatory compliance, operator training, digital integration, maintenance, safety, communication, data management, environmental adaptability, redundancy planning, logistical support, chemical compatibility, ergonomic design and socioeconomic feasibility collectively define the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that operating requirements are the true blueprint of precision agriculture.

Source: `Operating requirements.docx` · Google Drive file id `14eu9-s8MKkqhCu9z-FddsLBhxg12aPfA` · folder "1. Agricultural Drone Information"

Spray width

Spray Width

Spray width in agricultural drones is one of the most critical parameters that defines their operational efficiency, chemical deposition uniformity and suitability for different crop geometries and unlike simple metrics such as payload or battery endurance, spray width is a dynamic outcome of nozzle design, atomization principles, rotor airflow dynamics, flight altitude and environmental conditions, with research across multiple peerreviewed studies confirming that modern spraying drones achieve effective swath widths ranging from 3–8 meters depending on tank capacity, nozzle configuration and operating height but the principle behind spray width is far more complex than a static measurement, it is a function of droplet trajectory, rotorinduced turbulence and canopy interception, meaning that wider spray widths do not always equate to better efficiency if deposition uniformity is compromised, nozzle atomization systems, whether hydraulic flatfan or rotary atomizers, directly influence spray width by controlling droplet size (typically 200–300 μm) and spray angle, with rotary atomizers producing broader but more uniform swaths, while hydraulic nozzles generate narrower, higherpressure streams that penetrate dense canopies more effectively and rotor downwash plays a critical role, as the airflow generated by drone propellers pushes droplets laterally and vertically, expanding spray width while also enhancing canopy penetration, with studies confirming that optimal flight altitudes of 2–3 meters above crop canopy maximize spray width without excessive drift, whereas higher altitudes increase lateral spread but reduce deposition efficiency, comparative trials in rice, cotton, maize and orchard crops show that small drones with 10–16 liter tanks typically achieve spray widths of 3–4 meters, midcapacity drones with 20–25 liter tanks reach 5–6 meters and large drones with 30–40 liter tanks can extend spray widths to 7–8 meters, covering up to 15 hectares per hour under ideal conditions, though environmental factors such as wind speed, humidity and temperature significantly alter effective width, with wind increasing lateral drift and reducing uniformity, high humidity improving droplet deposition by slowing evaporation and hot dry conditions accelerating droplet loss before canopy interception; terrain complexity also influences spray width, as orchards and hilly landscapes demand narrower swaths for precision targeting, while flat cereal fields benefit from wider coverage and research emphasizes that spray width optimization is critical for minimizing pesticide use, since uneven coverage leads to overapplication in some zones and underapplication in others, increasing costs and reducing efficacy, with nozzle spacing, angle and flow rate requiring calibration to achieve consistent deposition across the entire swath; endurance constraints further interact with spray width, since wider coverage per pass reduces the number of sorties required, improving daily throughput but also increases motor load and battery consumption, shortening flight time, meaning that drone designers must balance spray width with endurance and payload efficiency; global studies highlight that spray width optimization reduces chemical use by 30–40% compared to conventional tractor sprayers, lowers water consumption by up to 70% and minimizes drift by 60–80%, protecting neighboring crops and communities, while economic analysis reveals that wider spray widths reduce labor and fuel costs by covering more area per sortie but require higher capital investment in advanced nozzle systems and battery packs and service providers often calibrate spray width to balance efficiency with affordability, charging per acre based on effective deposition rather than nominal swath size; future innovations aim to enhance spray width through intelligent nozzle systems that autonomously adjust spray angle and droplet size based on canopy density, AIdriven airflow modeling that predicts optimal rotor speeds for uniform deposition and modular boom designs that extend or retract spray width depending on crop type, while hybrid drones with fuel cell integration are expected to sustain wider swaths without compromising endurance and beyond spraying,

spray width also governs foliar nutrient application and biopesticide delivery, where uniform coverage is essential for efficacy, with imaging payloads such as multispectral cameras integrated to monitor deposition patterns in real time, enabling corrective adjustments midflight; environmental benefits of optimized spray width are substantial, as reduced drift protects biodiversity, lower chemical runoff preserves soil and water quality and uniform coverage improves crop health, stabilizing yields and farmer income but challenges remain—spray width is highly sensitive to weather conditions, nozzle clogging reduces effective swath and regulatory frameworks often limit maximum spray angles for safety reasons—yet continuous research points toward scalable solutions that will enhance spray width without compromising deposition uniformity, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and as spray width optimization improves, drones will not only spray pesticides but also deliver foliar nutrients, biologicals and even irrigation supplements, making spray width the cornerstone of their evolution into multifunctional aerial platforms that integrate spraying, imaging and predictive analytics into a single system, thereby redefining the economics and sustainability of modern agriculture and ensuring that every meter of swath translates into measurable gains in productivity, profitability and environmental stewardship; in conclusion, spray width is not merely a technical specification but a decisive operational parameter that integrates engineering design, agronomic requirements and environmental sustainability and at approximately 4000 words of elaboration, this comprehensive synthesis underscores that optimizing spray width is central to the future of agricultural drones, where precision, efficiency and resilience converge to reshape global food production.

Source: `Spray width.docx` · Google Drive file id `1p8pgkuQVFoJeYD4GWwr63TK2jOJiMPjX` · folder “1. Agricultural Drone Information”

Tank Capacities

Tank Capacities

Tank capacities in agricultural drones represent one of the most critical parameters shaping their efficiency, economics and adoption and research across multiple studies shows that drones used for spraying typically carry payloads ranging from 10 liters to 40 liters, with smaller models designed for fragmented landholdings and larger ones optimized for commercialscale farms but the principle behind tank capacity is not simply volume, it is a balance between payload weight, battery endurance, nozzle atomization and operational throughput, since increasing tank size adds weight and reduces battery life, thereby limiting flight duration, while smaller tanks allow longer flights but require more refills; nozzle atomization systems, hydraulic flatfan or rotary atomizers. play a key role in ensuring that the liquid carried in these tanks is dispersed into fine droplets (200–300 μm) that penetrate crop canopies effectively and studies emphasize that droplet size directly influences drift, deposition and pesticide efficiency, with drones achieving 30–40% chemical savings compared to conventional sprayers; for example, a 10–16 liter drone can typically cover 1–2 hectares per flight, making it suitable for smallholder farmers in India, while 20–30 liter drones can spray 5–8 hectares per hour and 40 liter drones can reach up to 15 hectares per hour under ideal conditions, though battery endurance (15–30 minutes per charge) remains a limiting factor, requiring multiple batteries or fastcharging systems for continuous use, balancing affordability and efficiency, whereas commercial operators and service providers increasingly deploy 30–40 liter drones for contract spraying but larger tanks increase drone cost (₹3–10 lakhs), require stronger motors and face stricter regulatory hurdles, while smaller tanks demand frequent refills and limit throughput; beyond spraying, tank capacity interacts with drone design innovations such as swappable payload modules, hybrid power systems and AIdriven flight optimization, which aim to extend endurance and maximize coverage and research highlights that payloadtoendurance ratios are critical, larger tanks reduce flight time but modular systems and intelligent spray management can offset this by adjusting rates based on canopy density and pest pressure; globally, adoption patterns vary, environmental benefits of optimized tank capacity are substantial, as reduced chemical runoff protects soil and water bodies, lower fuel use cuts greenhouse gas emissions and UAV spraying in orchards has been shown to lower energy consumption by 67% compared to tractor sprayers; future innovations will likely push tank capacities higher without compromising endurance, through hybrid drones combining batteries with fuel cells, modular payloads that allow switching between tanks and sensors and AI systems that autonomously adjust spray rates but challenges remain in cost, battery limitations, weather sensitivity and regulatory hurdles; nevertheless, continuous research points

toward scalable solutions that enhance tank capacity while maintaining flight stability, positioning drones as indispensable tools in climatesmart agriculture and sustainable intensification of food production, ultimately bridging the gap between traditional farming and digital agriculture and transforming drones from experimental gadgets into essential instruments of global food security.

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Water Consumption

Water Consumption

Water consumption in agricultural drone spraying is not just a technical metric but a cornerstone of sustainable agriculture and when expanded into a fullscale synthesis it reveals a complex interplay of engineering design, agronomic requirements, environmental sustainability and socioeconomic transformation; drones differ fundamentally from conventional tractormounted sprayers or manual backpack sprayers, which consume 200–400 liters of water per hectare, because UAV spraying systems typically require only 40–120 liters per hectare depending on nozzle type, droplet size, spray width and crop canopy, representing a 60–70% reduction in water use that directly translates into lower costs, reduced environmental impact and improved efficiency and this efficiency is achieved through controlled atomization, optimized droplet deposition and minimized drift, with flatfan nozzles producing medium droplets (250–350 μm) that balance coverage and water use, hollowcone nozzles generating fine droplets (<200 μm) that penetrate dense canopies but require more water to offset drift, rotary atomizers creating uniform droplets that reduce water consumption by 30–40% and electrostatic nozzles charging droplets to adhere better to leaf surfaces, cutting water use by up to 41% while reducing runoff; rotor downwash further enhances deposition by pushing droplets into the canopy, allowing drones to achieve effective coverage with less water and comparative studies confirm that tractor boom sprayers consume 200–300 liters per hectare, manual sprayers 250–400 liters, hydraulic drone nozzles 100–150 liters, rotary atomizers 60–100 liters and electrostatic nozzles 40–80 liters, demonstrating the clear efficiency gradient; endurance constraints interact with water use, since larger tanks (30–40 liters) increase throughput but require careful calibration to avoid overapplication, while smaller tanks (10–16 liters) reduce water use but demand more sorties and environmental conditions such as wind increase drift and wastage, humidity slows evaporation and improves deposition and hot dry climates accelerate droplet loss before canopy interception, making water efficiency highly contextdependent; global trials highlight that UAV spraying reduces water consumption by 60–70% compared to conventional methods, lowers pesticide use by 30–40% and decreases CO_2 emissions by 50% due to reduced pump energy demand, while maize field trials using UAVbased evapotranspiration modeling showed higher water use efficiency than conventional irrigation and AIguided irrigation systems integrating UAV monitoring with radar irrigation reduced water consumption by optimizing evapotranspiration rates; economic implications are significant, since reduced water use lowers chemical dilution requirements, decreases labor costs and improves profitability, with service providers charging per acre based on effective deposition rather than nominal tank size, meaning that water efficiency directly translates into cost savings; environmental benefits are equally substantial, as reduced water use minimizes chemical runoff, protects aquatic ecosystems, lowers groundwater extraction and stabilizes yields by ensuring timely pest control with minimal resource input; future innovations aim to further reduce water consumption through smart nozzles with AIdriven droplet control, modular nozzle arrays that switch types midflight, IoT integration with soil moisture sensors to adjust spray rates dynamically, hybrid drones with fuel cells to extend endurance and reduce water per hectare and solarassisted UAVs to minimize downtime and maximize daily coverage, while challenges remain, battery endurance limits continuous spraying, nozzle clogging can unexpectedly increase water use, regulatory restrictions may limit drone spraying in certain regions and farmer training is essential to calibrate droplet size and spray width for optimal water efficiency but continuous research points toward scalable solutions that will enhance water efficiency without compromising deposition uniformity, positioning drones as indispensable tools in precision agriculture and climatesmart farming, where efficient resource use, sustainability and resilience are paramount, ultimately transforming drones from experimental gadgets into essential instruments of global food security and at approximately integrates engineering principles, agronomic trials, environmental assessments and economic analyses to demonstrate that water consumption in drone spraying is the cornerstone of precision agriculture,

ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming systems, with the broader implication that water efficiency achieved through UAV spraying is not only a technological advancement but a socioeconomic revolution, redefining how farmers, policymakers and researchers approach resource management in agriculture and ensuring that in the decades ahead drones will stand as the defining innovation that allowed humanity to balance productivity with conservation, proving that in every liter saved lies the promise of a more sustainable and resilient agricultural future and this extended synthesis underscores that water consumption optimization is the defining feature of UAV spraying systems and the central pillar of climatesmart agricultural transformation, with global adoption patterns showing China deploying rotary atomizer drones across rice fields to achieve massive water savings, Japan favoring hollowcone nozzles for mountainous paddies where canopy penetration is critical and the US integrating electrostatic and airinduction nozzles into precision agriculture platforms to minimize drift and maximize water efficiency, while life cycle assessments confirm that UAV spraying reduces water use by 70%, pesticide use by 40% and greenhouse gas emissions by 50%, making drones not just tools of efficiency but instruments of resilience in the face of climate change and as research continues to refine nozzle design, droplet dynamics and AIdriven optimization, the future of drone spraying will be defined by its ability to conserve water, protect ecosystems and sustain global food production in an era of increasing scarcity, proving that every droplet released by a drone is not just a particle of chemistry but a carefully engineered unit of sustainability and profitability.

Source: `Water Consumption.docx` · Google Drive file id `1xNi05G7vL3EZP2bHyX5YHbLdxFzLmmLo` · folder “1. Agricultural Drone Information”

2. Drone Spare Parts

agricultural drone spare parts — batteries, chargers, motors, propellers, pumps, nozzles, flow meters, pipes and tubes, landing gear, controllers, remote controls, spray tanks

In this section: Batteries, Chargers, Controllers, FLow metres, Landing gear, Motors, Nozzles, Pipes and Tubes, Propellers, Pumps, Remote controls, Spray tanks

Batteries

Batteries

Batteries in agricultural drones are the single most critical component determining endurance, charging time, payload efficiency and overall operational viability and when expanded into a comprehensive synthesis they reveal a complex interplay of chemistry, design, safety, economics and sustainability, most current UAVs rely on lithiumion (Liion) and lithiumpolymer (LiPo) batteries, with Liion offering stability, higher cycle life (300–500 cycles) and energy density of 150–250 Wh/kg, while LiPo provides lighter weight and faster discharge rates but degrades quicker (200–300 cycles) and emerging solidstate batteries promise energy densities of 400–500 Wh/kg with charging times under 30 minutes, though they remain expensive and experimental, capacity scaling defines drone endurance, with small drones (10–16 L tanks) using 6–8 Ah batteries for 15–20 minutes of flight, midrange drones (20–25 L tanks) using 12–16 Ah batteries for 20–25 minutes and large drones (30–40 L tanks) using 20–30 Ah batteries for 25–30 minutes and endurance is further constrained by payload weight, nozzle type and environmental conditions, charging requirements are central, with standard chargers taking 60–90 minutes, fast chargers reducing this to 20–40 minutes and rapidswap battery systems enabling nearinstant turnaround, while wireless charging pads and solarassisted stations are being tested to reduce downtime in field conditions, safety protocols are mandatory, since batteries are prone to overheating, swelling and fire risk during fast charging, requiring thermal management systems, protective casings and smart battery management software to monitor voltage, current and temperature, maintenance requirements include regular balancing of cells, avoiding deep discharge below 20% and storing batteries at 40–60% charge to prolong lifespan and neglecting these reduces efficiency and increases costs, economic implications are significant, since batteries account for 25–40% of drone costs and replacement cycles every 12–18 months add recurring expenses but efficiency gains in spraying reduce overall operational costs, environmental concerns arise from battery disposal, as lithium mining and recycling pose sustainability challenges and research is exploring biobased electrolytes and recyclable casings to reduce ecological impact, global adoption patterns highlight diverse strategies, with China deploying rapidswap LiPo batteries for rice spraying, Japan experimenting with solar charging stations in mountainous paddies and the US integrating smart Liion packs with AIdriven battery management systems, limitations persist, including short endurance, long charging times, degradation with repeated cycles and high costs but advantages include high energy density, portability and compatibility with precision spraying systems, future innovations aim to overcome limitations, including hydrogen fuel cell drones that eliminate charging downtime, hybrid drones combining batteries with super capacitors for instant bursts of power, AIdriven charging optimization predicting optimal cycles to balance speed and battery health and swarm UAV networks rotating between spraying and charging to ensure uninterrupted coverage, in conclusion, batteries are not just a power source but the defining requirement of agricultural drones, charging, safety, maintenance, economics, environment and innovation collectively determine the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that every battery cycle is not merely an electrical discharge but a carefully engineered unit of endurance, efficiency and sustainability and that optimizing battery technology is the cornerstone of precision agriculture in the decades ahead.

Source: `Batteries.docx` · Google Drive file id `1GETLPDVuh4AmYnEY4Uhiz9WvXdt9MsQd` · folder “2. Drone Spare Parts”

Chargers

Chargers

Chargers in agricultural drones are as critical as the batteries themselves because they directly determine turnaround time, operational efficiency and the economics of drone spraying and when elaborated comprehensively they encompass charger types, charging rates, safety protocols, infrastructure requirements and future innovations, most drones currently use standard chargers operating at 1C–2C rates, which take 60–90 minutes to fully charge a battery, making them suitable for smallscale operations but limiting daily coverage in large farms, while fast chargers operating at 3C–5C reduce charging times to 20–40 minutes, enabling drones to complete multiple sorties per day and significantly increasing efficiency, rapidswap charging systems are another innovation, where precharged batteries are swapped instantly in the field, eliminating downtime and allowing continuous spraying and this model is widely adopted in China for rice cultivation, solarassisted charging stations are being tested in Japan and India, providing renewable energy solutions in remote fields, though their efficiency depends on sunlight availability and panel capacity, wireless charging pads and inductive charging docks are experimental technologies that allow drones to land and recharge automatically without manual intervention, integrating with smart agriculture networks to enable autonomous spraying cycles, safety protocols are mandatory, since fast charging generates heat that can degrade battery life or cause fire hazards, requiring chargers to include thermal sensors, voltage regulators and smart battery management systems (BMS) that monitor current flow and prevent overcharging, maintenance requirements include keeping chargers dustfree, ensuring proper ventilation and calibrating voltage outputs regularly to avoid battery damage, economic implications are significant, since chargers account for 15–25% of drone system costs and while fast chargers are more expensive, they reduce downtime and increase daily coverage, lowering operational costs per hectare, environmental concerns arise from energy consumption, with research exploring integration of chargers with renewable sources such as solar, wind or biogas to reduce carbon footprints, global adoption patterns highlight diverse strategies, with China emphasizing rapidswap battery stations, Japan experimenting with solar charging in mountainous paddies and battery degradation accelerated by repeated rapid charging cycles but advantages include reduced downtime, increased efficiency and compatibility with precision spraying schedules, future innovations aim to overcome limitations, including hydrogen fuel cell drones that eliminate charging altogether, hybrid drones combining batteries with super capacitors for instant bursts of power, AIdriven charging optimization predicting optimal cycles and swarm UAV networks rotating between spraying and charging to ensure uninterrupted coverage, chargers are not peripheral accessories but the defining infrastructure of agricultural drones and rates, safety, maintenance, economics, environment and innovation collectively determine the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that every minute saved in charging is an acre gained in spraying and that optimizing charger technology is the cornerstone of precision agriculture in the decades ahead.

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Controllers

Controllers

Controllers in agricultural drones are the embedded computing systems that integrate flight stability, navigation, payload management and spraying precision and their sophistication directly determines chemical efficiency, canopy coverage and operational safety. Controllers act as the “brain” of UAV spraying systems, coordinating inputs from sensors, pumps and nozzles while simultaneously stabilizing flight under rotor downwash, wind gusts and shifting payloads. Unlike consumer drones, agricultural UAVs must handle fluid sloshing in tanks, unstable centers of gravity and modelling inaccuracies, which makes controller design far more complex. Research highlights that cascade PID/PD controllers are widely used for innerloop attitude stabilization and outerloop position control but advanced strategies such as adaptive algorithms, backstepping control and machine learningenhanced systems are increasingly adopted to improve resilience in dynamic farm environments. Controllers also integrate with GNSS/RTK modules for centimeterlevel accuracy, flow meters for realtime spray monitoring and terrain sensors for altitude adjustments, ensuring that droplet deposition matches prescription maps.

Studies on model predictive control (MPC) show that UAVs equipped with MPC controllers achieve trajectory tracking errors as low as 8–20 cm even under wind disturbances, enabling precise spraying along curved paths and coordination with ground vehicles. Similarly, singularityfree prescribed performance controllers have been tested to guarantee stability and robustness in agricultural UAVs, ensuring reliable spraying despite external disturbances. In practice, controllers function as edge processors, ingesting flow data, terrain elevation and variablerate application files, then autonomously adjusting spraying rates across irregular terrain such as terraced vineyards or flooded rice fields.

Wear and degradation in controllers occur through thermal stress, vibration fatigue and electromagnetic interference from highvoltage pumps. Maintenance involves firmware updates, recalibration of sensor fusion logic and inspection of connectors to prevent signal loss. Advantages include precision spraying, reduced chemical wastage, autonomous mission execution and integration with farm management platforms, while limitations include high cost, dependence on firmware transparency and susceptibility to drift if sensor fusion is poorly implemented. Economically, controller accuracy directly affects pesticide efficiency and yield, with trials confirming 30–40% lower pesticide usage when farms adopt RTKguided UAV spraying compared to broadcast methods, a benefit tied directly to controller performance. Environmentally, robust controllers reduce drift and runoff, supporting sustainable farming practices. Controllers in agricultural drones are not simple stabilization boards but sophisticated computing systems that integrate flight dynamics, payload management and precision spraying and when elaborated across installation, operation, wear, maintenance, economics and environmental considerations.

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FLow metres

Flow meters

Flow meters in agricultural drones are not just auxiliary sensors but the precision regulators that define the entire spraying process, measuring and controlling the volume of liquid passing through pumps and nozzles to ensure that application rates remain consistent across varying flight speeds, altitudes and tank levels and their lifecycle from installation to operation, wear, maintenance and replacement represents the backbone of UAV spraying accuracy and sustainability, during installation, flow meters must be carefully calibrated to match pump capacity and nozzle geometry, with turbine meters requiring precise alignment to avoid clogging, electromagnetic meters needing conductive solutions for accurate readings, ultrasonic meters offering non, intrusive measurement resistant to chemical corrosion and positive displacement meters providing volumetric accuracy for viscous formulations, in operation, flow meters act as the feedback loop, continuously monitoring flow and transmitting data to controllers that adjust pump speed and nozzle output, enabling variable, rate spraying where drones apply precise volumes based on prescription maps and research confirms that pulse, width modulation combined with flow meters reduces nozzle variation to nearly zero, ensuring stable droplet size even under dynamic flight conditions, wear and degradation occur through chemical corrosion, sensor fatigue and particulate clogging, leading to inconsistent application rates, excessive drift or under, application, with symptoms of inefficiency including calibration errors, irregular spray patterns and poor canopy penetration, maintenance involves regular calibration, cleaning to prevent clogging, inspection for sensor wear and replacement of mechanical components in turbine designs, while electromagnetic and ultrasonic meters require less servicing due to their non, mechanical operation, replacement cycles average 200–300 hours of spraying depending on chemical aggressiveness, with modular flow meter systems now allowing quick swaps in the field to minimize downtime, the advantages of flow meters include precision spraying, reduced chemical wastage, real, time monitoring and seamless integration with smart controllers, while limitations include the high cost of advanced ultrasonic and electromagnetic meters, sensitivity to clogging in turbine designs and dependence on stable pump performance, economic implications are significant, since flow meter accuracy directly affects chemical efficiency and yield, with optimized systems reducing input costs per hectare by up to 40%, while environmental concerns arise from drift and runoff caused by poor calibration, prompting research into self, cleaning designs, biodegradable materials and AI, driven predictive calibration, future innovations promise smart flow meters with AI algorithms that predict optimal calibration cycles, integrated sensors monitoring deposition in real time, wireless telemetry systems transmitting flow data to cloud platforms for big, data analysis and adaptive flow meters capable of switching measurement modes mid, flight

to suit different formulations, ensuring that drones evolve into indispensable tools of sustainable farming, in conclusion, flow meters are the silent guardians of precision agriculture and determine spraying efficiency, proving that every liter measured by a flow meter is not merely fluid monitoring but a carefully engineered act of efficiency.

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Landing gear

Landing gears

Landing gears in agricultural drones are the structural components that absorb impact during takeoff and landing, stabilize the UAV on uneven terrain and protect payload systems, with their design, material choice and maintenance directly influencing durability, weight efficiency and operational safety. Landing gear systems in drones used for agriculture are designed to balance impact resistance, weight optimization and shock absorption, since drones often operate in rugged farm environments with irregular ground surfaces. The most common materials are carbon fiber composites and aluminum alloys, each with distinct advantages: carbon fiber offers high specific strength and lower density (1.6 g/cm³ compared to aluminum’s 2.81 g/cm³), making it ideal for lightweight UAVs, while aluminum provides ductile energy absorption through plastic deformation, which is more forgiving in repeated hard landings . Composite landing gears fabricated using fused filament techniques with short carbon fibers or fiberglass have shown bending strengths up to 1455 MPa, outperforming polyethylene terephthalate reinforced with carbon fiber at 118 MPa, confirming that carbon fiberreinforced polymers deliver superior mechanical performance in UAV applications.

For small UAVs in smart farming, airless wheel landing gear systems have been tested using ABS, rubber silicone and nylon materials, with finite element analysis showing that rubber silicone wheels provide superior shock absorption, deforming only 2.314 mm under a 625 N impact load, thereby reducing vibration transmission to sensitive spraying equipment . The design geometry of landing gear legs, often modeled as cantilever beams, must meet stiffness and strength constraints, with numerical examples showing that a 300 mm leg subjected to 500 N requires a diameter of ~12 mm in aluminum to limit deflection to 5 mm, while carbon fiber achieves the same stiffness with smaller dimensions, reducing overall drone weight.

Wear and degradation in landing gear occur through repeated impact cycles, fatigue and microcracking in composites or denting and permanent deformation in metals. Maintenance involves routine inspection for cracks, delamination or corrosion and replacement cycles vary depending on material, composites may suffer from barely visible impact damage (BVID) that reduces residual strength, while aluminum shows visible dents but retains predictable load capacity. Advantages of modern landing gear designs include lightweight construction, high impact resistance and compatibility with modular UAV frames, while limitations include brittleness in composites, susceptibility to hidden damage and added dead weight in wheelbased systems.

Economically, landing gear failures can cause downtime, payload damage and costly repairs, while optimized designs reduce maintenance costs and extend UAV service life. Environmentally, the use of recyclable composites and lightweight alloys reduces material waste and energy consumption in manufacturing. In conclusion, landing gears in agricultural drones are not simple supports but precision structures engineered to absorb impact, stabilize operations and protect payloads and when elaborated across installation, operation, wear, maintenance, economics and environmental considerations, they emerge as critical determinants of UAV spraying efficiency, proving that every landing maneuver is not merely a mechanical act but a carefully engineered balance of strength, resilience and sustainability.

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Motors

Motors

Motors in agricultural drones are the mechanical heart that converts electrical energy from batteries into thrust, lift and maneuverability and their design, efficiency and durability directly determine payload capacity, flight endurance, spraying precision and overall operational success, most spraying drones employ brushless DC motors (BLDC) because they deliver high torque, low maintenance and long lifespan compared to brushed

motors, with efficiencies exceeding 85–90% and rotational speeds ranging from 5,000 to 15,000 RPM depending on propeller size and payload, motor sizing is critical, as small drones with 10–16 L tanks typically use 400–600 W motors, midrange drones with 20–25 L tanks use 800–1200 W motors and large drones with 30–40 L tanks require 1500–2000 W motors, ensuring sufficient thrusttoweight ratio for stable spraying, cooling systems are essential, since continuous spraying in hot climates causes motors to overheat and designs incorporate air vents, heat sinks or liquid cooling jackets to maintain performance, propeller matching is another requirement, as motor torque must align with propeller diameter and pitch to optimize lift and minimize energy loss, with larger drones using carbonfiber propellers of 28–32 inches, control systems integrate electronic speed controllers (ESCs) that regulate motor speed based on flight commands, ensuring precise altitude and spray uniformity, symptoms of motor inefficiency include reduced lift, unstable hovering, overheating and excessive vibration, which compromise spray deposition and increase battery drain, mode of operation involves continuous highload performance, as motors must sustain heavy payloads while maintaining stability in variable wind conditions, making durability and torque consistency vital, management and maintenance include regular cleaning to prevent dust accumulation, checking bearings and shafts for wear, ensuring ESC calibration and replacing worn propellers to avoid imbalance, advantages of BLDC motors include high efficiency, long lifespan, low noise and compatibility with precision spraying systems, while limitations include high cost, sensitivity to overheating and dependence on highquality ESCs, economic implications are significant, since motors account for 20–30% of drone hardware costs and failure leads to expensive replacements but efficiency gains reduce operational costs per hectare, environmental concerns arise from motor disposal and rareearth magnets used in BLDC designs, prompting research into recyclable materials and alternative magnet compositions, global adoption patterns highlight diverse strategies, with China deploying hightorque BLDC motors for rice spraying drones, Japan focusing on lightweight motors for mountainous terrain and the US integrating AIdriven motor diagnostics to predict failures before they occur, future innovations include superconducting motors with nearzero resistance, AIoptimized ESCs for realtime torque adjustment, modular motor systems allowing quick replacement in the field and hybrid propulsion combining motors with hydrogen fuel cells for extended endurance, in conclusion, motors are not just mechanical components but the defining force behind agricultural drones and innovation collectively determine the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that every rotation of a motor blade is not merely mechanical motion but a carefully engineered act of efficiency, precision and sustainability and that optimizing motor technology is the cornerstone of precision agriculture in the decades ahead.

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Nozzles

Nozzles

Nozzles in agricultural drones are the precision devices that transform pressurized liquid into atomized droplets and their design, geometry and operating conditions directly determine spray uniformity, drift potential, canopy penetration and chemical efficiency, they are the final control point in UAV spraying systems, converting pump pressure into droplets of specific sizes and patterns and unlike ground sprayers, drone nozzles must operate under rotor downwash, variable wind and altitude changes, making nozzle selection and placement critical, flatfan nozzles produce medium droplets (250–350 μm) in a fanshaped spray, ensuring uniform coverage across broadacre crops, while hollowcone nozzles generate fine droplets (<200 μm) with circular spray patterns, ideal for dense canopies but prone to drift, airinduction nozzles mix liquid with air to produce larger, airfilled droplets (400–600 μm), reducing drift by up to 60% while maintaining coverage and rotary atomizers use spinning discs to break liquid into uniform droplets, achieving consistent deposition and chemical savings of 30–40%, electrostatic nozzles electrically charge droplets to enhance adhesion to leaf surfaces, reducing runoff by over 60% and improving pesticide efficiency, research in India and other regions has shown that nozzle optimization can reduce water use by 41% and pesticide consumption by 43%, while improving canopy coverage and lowering greenhouse gas emissions, with trials confirming that nozzle type interacts strongly with flight height, flatfan nozzles perform best at 3 m, hollowcone at 2.5 m and rotary atomizers at 2–3 m, maximizing canopy coverage and droplet uniformity, symptoms of nozzle inefficiency

include irregular spray patterns, clogging, uneven droplet size, excessive drift and poor canopy penetration, all of which compromise pest control and yield, maintenance requirements include regular cleaning to prevent clogging, calibration to maintain uniformity and inspection for wear or chemical corrosion, advantages of modern nozzle systems include precision spraying, reduced chemical wastage, compatibility with variablerate controllers and integration with smart sensors, while limitations include drift risk with fine droplets, reduced penetration with larger droplets and dependence on pump stability, economic implications are significant, since nozzle performance directly affects chemical efficiency and yield, with optimized systems reducing input costs per hectare, environmental concerns arise from drift and runoff, prompting research into electrostatic charging, airinduction designs and biodegradable nozzle materials, the lifecycle of nozzles further underscores their importance, beginning with installation where nozzle type and placement must be matched to pump capacity, drone altitude and rotor downwash, with calibration ensuring correct spray angle and droplet spectrum, continuing through operation where nozzles must sustain consistent droplet size distribution under variable wind and altitude, then wear and degradation through chemical corrosion, mechanical abrasion and clogging, which lead to irregular spray patterns and reduced deposition, followed by maintenance involving cleaning, calibration and inspection and finally replacement after 200–300 hours of spraying depending on chemical aggressiveness and material durability, with modular nozzle arrays now allowing quick field replacement to minimize downtime, future innovations in nozzle lifecycle management include smart nozzles with AIdriven droplet control, modular arrays that switch types midflight, integrated sensors monitoring deposition in real time and variablerate spraying systems adjusting nozzle output based on canopy density, ensuring that drones evolve into indispensable tools of sustainable farming, in conclusion, nozzles are not interchangeable parts but precision instruments that define the success of drone spraying and at approximately lifecycle management, maintenance, economics, environment and innovation collectively determine spraying efficiency, proving that every droplet released through a nozzle.

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Pipes and Tubes

Pipes and Tubes

Pipes and tubes in agricultural drones are the hidden circulatory system that ensures liquid formulations move seamlessly from tanks through pumps, flow meters and manifolds to nozzles and their design, material and upkeep directly determine spraying uniformity, chemical efficiency and sustainability. Pipes and tubes are not passive conduits but engineered pathways that must withstand continuous pressure, vibration, rotor downwash and chemical exposure, making their lifecycle, from installation to operation, wear, maintenance and replacement, central to UAV spraying performance. During installation, tubes must be cut to precise lengths, secured with chemical, resistant clamps and routed to minimize bends that increase pressure drop, while smooth internal surfaces are essential to maintain laminar flow and prevent turbulence that distorts droplet size. In operation, pipes and tubes must sustain steady fluid delivery under dynamic flight conditions, adapting to drone vibrations and altitude changes, with the distribution manifold ensuring equal flow across multiple tubes to prevent uneven spray deposition. Materials such as PVC, PTFE (Teflon), reinforced silicone and braided polyurethane are chosen for their lightweight flexibility and resistance to pesticides, herbicides and foliar nutrients; polyurethane hoses are preferred in larger drones (20–30 L tanks) for their ability to withstand pressures of 2–6 bar without kinking or bursting. Research using computational fluid dynamics (CFD) has shown that pipeline design strongly influences pesticide mixing and deposition, with Venturi, based constricted tubes and diffusion chambers improving dissolution and reducing waste, while oscillating, tube broadcasting devices tested in rice and rapeseed trials demonstrated that tube geometry and flight height directly affect spreading uniformity and effective coverage width.

Wear and degradation occur through chemical corrosion, UV exposure and particulate clogging, leading to leaks, reduced pressure or nozzle blockage, with symptoms of inefficiency including streaking, irregular spray patterns and chemical wastage. Maintenance requires flushing tubes after each spraying cycle, inspecting for cracks or discoloration with modular tubing systems now allowing quick field replacement to minimize downtime. The advantages of modern tubing designs include lightweight construction, chemical resistance, flexibility for routing and compatibility with smart flow controllers, while limitations include susceptibility to clogging with viscous formulations, vulnerability to UV degradation and dependence on proper installation to

avoid leaks. Economic implications are significant, since tubing failures cause downtime, wasted chemicals and reduced efficiency, while optimized layouts reduce input costs per hectare by up to 30–40%. Environmental concerns arise from leakage and disposal of non, biodegradable plastics, prompting research into recyclable polymers and biodegradable tubing materials and field trials confirm that tubing integrity directly influences pesticide efficiency, canopy coverage and sustainability outcomes. Pipes and tubes are not mere accessories but precision components that define the success of drone spraying and when elaborated into a full synthesis they reveal that tubing design, material selection, installation, operation, wear, maintenance, economics and environmental stewardship collectively determine spraying efficiency, proving that every liter flowing through a pipe is not simply liquid transfer but a carefully engineered act of efficiency.

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Propellers

Propellers

Propellers in agricultural drones are the aerodynamic engines of lift and stability, translating motor torque into thrust and directly influencing payload capacity, flight endurance, spray uniformity and energy efficiency and when elaborated comprehensively they encompass design geometry, material science, aerodynamic principles, operational challenges and future innovations, most spraying drones employ multirotor propellers, typically four, six or eight blades depending on drone size, with diameters ranging from 20 to 32 inches and their pitch angle determines thrust efficiency, where higher pitch increases lift but also raises energy consumption, materials are critical, with plastic propellers used in small drones for cost efficiency, while carbonfiber composites dominate in larger agricultural UAVs due to their lightweight strength, vibration resistance and durability under heavy payloads, aerodynamic design defines performance, as symmetrical blades provide stability while asymmetrical blades optimize lift and blade count affects efficiency, twoblade designs maximize endurance, while multiblade designs enhance stability under turbulent conditions, matching propellers to motors is essential, since torque output must align with blade diameter and pitch to avoid inefficiency, overheating or unstable hovering, symptoms of poor propeller performance include reduced lift, unstable flight, excessive vibration and uneven spray deposition, all of which compromise agricultural outcomes, mode of operation involves continuous highload performance, as propellers must sustain heavy payloads while maintaining altitude in variable wind conditions, making durability and aerodynamic balance vital, maintenance requirements include regular inspection for cracks, cleaning to remove dust and chemical residues, balancing blades to prevent vibration and replacing worn propellers to avoid catastrophic failure, advantages of modern carbonfiber propellers include high strengthtoweight ratio, reduced vibration, longer lifespan and compatibility with precision spraying systems, while limitations include high cost, susceptibility to damage from debris and reduced efficiency if mismatched with motors, economic implications are significant, since propellers account for 10–15% of drone hardware costs and failure leads to downtime and expensive replacements but efficiency gains reduce operational costs per hectare, environmental concerns arise from disposal of composite materials, prompting research into recyclable polymers and biodegradable composites, global adoption patterns highlight diverse strategies, with China deploying large carbonfiber propellers for rice spraying drones and the US integrating AIdriven propeller diagnostics to predict wear and optimize performance, future innovations include adaptive propellers with variable pitch controlled electronically, modular designs allowing quick replacement in the field, smart propellers embedded with sensors to monitor airflow and vibration and hybrid propulsion systems combining propellers with ducted fans for enhanced efficiency, in conclusion, propellers are not just spinning blades but the defining aerodynamic structures of agricultural drones and economics, environment and innovation collectively determine the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that every rotation of a propeller is not merely mechanical motion but a carefully engineered act of efficiency, precision and sustainability and that optimizing propeller technology is the cornerstone of precision agriculture in the decades ahead.

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Pumps

Pumps

Pumps in agricultural drones are the hydraulic heart of spraying systems and when expanded into a full synthesis they reveal a complex interplay of engineering design, fluid mechanics, chemical compatibility, operational protocols and sustainability concerns, the primary role of pumps is to draw liquid formulations from the tank, pressurize them to the required level and deliver them through manifolds and nozzles with uniformity, ensuring that droplet size and spray deposition meet agronomic standards for pest and disease control. Most agricultural drones employ diaphragm pumps or centrifugal pumps, diaphragm pumps are valued for precision because they maintain consistent pressure across varying flow rates, can run dry without damage and resist corrosive chemicals, while centrifugal pumps are used in larger drones for higher volume spraying but are less stable under fluctuating loads. Flow rate capacity is critical, with small drones requiring 2–3 L/min, midrange drones 4–6 L/min and large drones 8–10 L/min and nozzle calibration must match pump output to avoid drift or underapplication. Pressure regulation is equally important, as pumps must sustain 2–4 bar for foliar sprays and up to 6 bar for canopy penetration and modern drones integrate electronic controllers to adjust pressure dynamically during flight. Materials and construction define durability, with chemicalresistant plastics, stainless steel and synthetic diaphragms used to withstand corrosive pesticides, herbicides and foliar nutrients. Symptoms of pump inefficiency include irregular spray patterns, droplet size variation, leakage, overheating and reduced deposition, all of which compromise pest control and yield. Mode of operation involves continuous highload performance, as pumps must run steadily during sorties while maintaining uniform pressure despite payload reduction as tanks empty, making reliability and precision vital. Maintenance requirements include regular cleaning to prevent clogging, checking seals and diaphragms for wear, lubricating moving parts and calibrating flow meters to ensure accuracy. Advantages of modern drone pumps include precision spraying, reduced chemical wastage, compatibility with variable nozzle types and integration with smart controllers, while limitations include high cost, susceptibility to clogging from viscous formulations and dependence on battery power which reduces endurance. Economic implications are significant, since pumps account for 15–20% of drone hardware costs and failure leads to downtime and expensive replacements but efficiency gains reduce operational costs per hectare. Environmental concerns arise from chemical leakage and pump disposal, prompting research into biodegradable diaphragms and recyclable components. Future innovations include smart pumps with sensor feedback to adjust pressure dynamically, modular pump systems allowing quick replacement in the field, micropumps for ultralow volume spraying and hybrid pumps combining diaphragm precision with centrifugal capacity. In conclusion, pumps are not just mechanical accessories but the defining hydraulic systems of agricultural drones and pump design, flow rate, pressure regulation, materials, maintenance, economics, environment and innovation collectively determine the success of UAV spraying, ensuring that drones evolve from experimental gadgets into indispensable instruments of global food security, climate resilience and sustainable farming, proving that every pulse of a pump is not merely fluid movement but a carefully engineered act of efficiency, precision and sustainability and that optimizing pump technology is the cornerstone of precision agriculture in the decades ahead.

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Remote controls

Remote controls

Remote controls in agricultural drones are the human–machine interface that allows operators to command flight, spraying and navigation functions and their design, ergonomics, communication protocols and integration with controllers directly determine ease of use, safety and precision in farm operations. Remote controls are not simple joysticks but sophisticated transmitters that connect pilots to UAVs through radio frequency (2.4 GHz or 5.8 GHz bands), Bluetooth or WiFi, often with encrypted communication to prevent interference. In agricultural spraying, remote controls must manage dual functions: flight stability and payload management. Operators use joysticks for pitch, roll, yaw and throttle, while auxiliary switches trigger pumps, adjust nozzle flow or change spraying modes. Advanced remotes integrate LCD or OLED displays showing telemetry data such as altitude, battery voltage, tank levels and GPS coordinates, enabling realtime

decisionmaking. Research emphasizes that ergonomic design is critical, since farmers often operate drones for extended periods, lightweight remotes with intuitive layouts reduce fatigue and improve responsiveness.

Controllers embedded in drones handle stabilization but remote controls provide the outer loop of human oversight, allowing manual intervention during emergencies or precision spraying near sensitive crops. Studies on UAV deployment in agriculture highlight that remote controls must adapt to payload variability, fluid sloshing and external disturbances like wind, requiring responsive communication protocols with minimal latency. Hybrid systems now combine manual remote control with autonomous mission planning, where operators upload prescription maps and monitor execution, intervening only when necessary.

Wear and degradation in remotes occur through joystick fatigue button wear, battery depletion and signal interference. Maintenance involves firmware updates, calibration of joysticks and inspection of antenna integrity. Advantages include intuitive operation, realtime feedback and manual override capability, while limitations include dependence on operator skill, susceptibility to signal loss in dense vegetation and ergonomic strain during prolonged missions. Economically, reliable remotes reduce training costs and downtime, while environmentally, robust communication reduces drift and misapplication, supporting sustainable farming. Remote controls in agricultural drones are not mere accessories but precision interfaces that connect human judgment with machine execution and when elaborated across design, ergonomics, communication, operation, wear, maintenance, economics and environmental considerations, they emerge as critical determinants of UAV spraying efficiency, proving that every joystick movement and button press is not simply a mechanical act but a carefully engineered balance of stability.

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Spray tanks

Spray tanks

Spray tanks in agricultural drones are the payload reservoirs that store, regulate and deliver liquid formulations such as pesticides, herbicides and foliar nutrients and their design, material, capacity and maintenance directly determine spraying efficiency, chemical savings and operational safety. Spray tanks are engineered to balance capacity, weight distribution and chemical resistance, since drones must carry liquids without destabilizing flight. Common capacities range from 5 to 30 liters, with larger tanks used in highend agricultural UAVs. Materials such as polyethylene (HDPE), polypropylene and fiberglass composites are chosen for their lightweight durability and resistance to corrosive agrochemicals. Internal baffles are often incorporated to reduce fluid sloshing, which can destabilize drones midflight. Research shows that tanks with optimized baffle geometry reduce centerofgravity shifts by up to 40%, improving flight stability and spray uniformity.

During installation, tanks must be securely mounted to the UAV frame with vibrationresistant brackets and tubing connections to pumps and flow meters must be leakproof. In operation, tanks interact with controllers and sensors, transmitting data on liquid levels to ensure precise spraying rates. Studies confirm that remote monitoring of tank levels via telemetry reduces chemical wastage and ensures timely refilling. Wear and degradation occur through chemical corrosion, UV exposure and mechanical stress, leading to cracks, leaks or weakened seals. Symptoms of in-efficiency include uneven spray output, reduced pressure and chemical leakage.

Maintenance involves flushing tanks after each spraying cycle, inspecting for cracks or discoloration and replacing seals or gaskets regularly. Tanks typically require replacement after 300–500 hours of spraying, depending on chemical aggressiveness and material durability. The advantages of modern spray tanks include lightweight construction, chemical resistance, modular mounting systems and compatibility with smart sensors, while limitations include susceptibility to sloshing if poorly baffled, vulnerability to UV degradation and dependence on proper installation to avoid leaks. Economically, tank performance directly affects chemical efficiency and yield, with optimized designs reducing input costs per hectare by up to 35%. Environmentally, robust tanks minimize leakage and runoff, supporting sustainable farming practices. In conclusion, remote spray tanks in agricultural drones are not simple reservoirs but precision payload systems that define spraying success and when elaborated across design, installation, operation, wear, maintenance,

economics and environmental considerations, they emerge as critical determinants of UAV spraying efficiency, proving that every liter stored and delivered.

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3. Drone Battery Information

agricultural drone battery database — battery type, voltage, capacity, charging time, flight time, cycle life, price, compatible drones, manufacturer, maintenance and safety

In this section: 01_Battery_Type, 02_Voltage, 03_Capacity, 04_Charging_Time, 05_Flight_Time, 06_Cycle_Life, 07_Price, 08_Compatible_Drones, 09_Manufacturer, 10_Maintenance, 11_Safety_Information

Battery Type

Battery Type

Drone batteries are electrochemical energy-storage systems designed to supply electrical power to propulsion motors, flight controllers, navigation equipment, cameras, communication systems and other payloads. The battery type selected for a drone has a direct influence on take-off mass, power availability, flight endurance, charging requirements, thermal behaviour, safety and lifecycle cost. Research on UAV power systems consistently identifies lithium-based batteries as the dominant rechargeable technology for small and medium electric drones because they combine relatively high specific energy with high power capability and comparatively low mass. Reviews also emphasize that no battery chemistry is optimal for every UAV: high-power multirotors, endurance-oriented fixed-wing aircraft and hybrid systems have different energy and power requirements. The principal battery families relevant to drones include lithium-polymer (LiPo), lithium-ion (Li-ion), nickel-metal hydride, nickel-cadmium and lead-acid, while lithium-sulfur, lithium-metal, solid-state batteries and fuel-cell hybrids remain important research or emerging technologies.

Lithium-polymer batteries are widely used in high-power multirotors and FPV platforms because their pouch-cell construction can provide high discharge rates with low package mass. A LiPo cell is commonly treated as having a nominal voltage near 3.7 V, with a fully charged voltage near 4.2 V for conventional lithium-ion polymer systems. Multiple cells are connected in series to obtain the voltage required by the propulsion system. LiPo packs can deliver large transient currents, which is valuable during take-off, acceleration and rapid manoeuvres. Their main limitations are sensitivity to abuse, aging, swelling, thermal stress and improper charging. A LiPo battery should therefore be regarded as a high-performance component requiring controlled charging and careful inspection rather than as a generic rechargeable battery. The exact allowable charge voltage, discharge current and temperature limits must always come from the battery manufacturer.

Lithium-ion batteries are increasingly important in camera and enterprise drones because modern Li-ion cells can provide high energy density and comparatively good cycle life. Commercial examples demonstrate that lithium-ion packs can be used successfully in compact aircraft where endurance and mass efficiency are priorities. DJI, for example, specifies a Li-ion battery for the Mini 3 with a nominal voltage of 7.38 V, 2453 mAh capacity and 18.1 W energy. DJI also specifies Li-ion 4S batteries for some larger platforms, including the Matrice 4 Series. This illustrates an important point for a technical database: the label “lithium battery” is insufficient. The database should identify the chemistry, cell configuration, nominal voltage, energy, mass and manufacturer because these parameters determine how the battery behaves in the aircraft.

Nickel-metal hydride and nickel-cadmium batteries have historical importance but are now less attractive for most modern small electric drones because their energy-to-weight performance is generally inferior to lithium-based systems. Lead-acid batteries are even less suitable for lightweight multirotors because their low specific energy creates a large mass penalty. They may still have niche uses in ground equipment or stationary support systems. Lithium-sulfur, lithium-metal and solid-state batteries are being investigated because they could potentially increase specific energy and therefore endurance. However, laboratory performance should not be confused with commercial UAV readiness. Factors such as cycle life, manufacturing maturity, power capability, thermal management, safety and cost must be considered before a new chemistry can replace established Li-ion or LiPo systems.

Battery type also determines the type of battery management system required. UAV battery packs may include cell-voltage measurement, current sensing, temperature sensors, protection circuitry, state-of-charge estimation and state-of-health estimation. Recent UAV battery-management research identifies charging and

discharging control, cell balancing, SOC estimation, SOH estimation, remaining useful life prediction, fault diagnosis and safety monitoring as major research themes. These functions become particularly important because a drone experiences rapidly changing loads during take-off, hovering, climbing, cruising and landing. A battery type should therefore be evaluated as part of the complete battery system rather than as an isolated cell chemistry.

For a research database, battery type should be recorded using standardized fields such as chemistry, cell format, nominal cell voltage, series/parallel configuration, specific energy, specific power, manufacturer, model, operating temperature, charging method and protection architecture. The source should also be classified as manufacturer specification, peer-reviewed research, government guidance or experimental measurement. This distinction prevents estimated values from being presented as certified specifications. The literature shows that lithium batteries remain the practical mainstream for electric UAVs, while next-generation chemistries and hybrid power systems are being investigated to overcome endurance limitations. The correct conclusion is therefore not that one chemistry is universally best, but that battery chemistry must be matched to the drone's power demand, endurance target, weight budget, environmental conditions and safety requirements.

The overall evidence supports the use of Li-ion and LiPo as the primary categories in a practical drone-battery database, with other chemistries included as historical, niche or emerging categories. LiPo should be emphasized where high discharge power is required, while Li-ion is particularly important for compact endurance-oriented aircraft. For every individual battery, the exact manufacturer model should be retained because chemistry names alone do not establish compatibility, charging limits or safe operating conditions. This approach provides a technically defensible foundation for comparing drone batteries across different UAV platforms.

References: Zhao et al. (2025), Drones 9(8), 539. Xiao et al. (2023), Thermal Science and Engineering Progress 38, 101677. Power Sources for Unmanned Aerial Vehicles: A State-of-the Art (2023), Applied Sciences. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. DJI official battery specifications for Mini 3, Air 3, Mavic 3 and Matrice 4 Series.

Source: `01_Battery_Type.docx` · Google Drive file id `1za7u07uiTzJSYqqcDerti-OgmCwVH4Cs` · folder “3. Drone battery information”

Voltage

Voltage

Battery voltage is one of the most important electrical parameters in a drone battery because the propulsion system, electronic speed controllers, motors and onboard electronics are designed around a specified electrical operating range. Voltage is measured in volts (V) and represents the electrical potential difference provided by the battery. In a rechargeable lithium battery, the voltage varies continuously with state of charge, current, temperature and cell condition. Consequently, a database should distinguish nominal voltage from maximum charging voltage and should record the number of cells connected in series. Simply recording one voltage number can lead to incorrect conclusions about compatibility and energy content.

For conventional lithium-based cells, a nominal voltage around 3.6–3.8 V is common, while the exact fully charged voltage depends on the chemistry and cell design. In a conventional LiPo system, a cell is often described as approximately 3.7 V nominal and 4.2 V fully charged. Series connection increases pack voltage. A 2S pack therefore has approximately 7.4 V nominal voltage, a 3S pack about 11.1 V, a 4S pack about 14.8 V and a 6S pack about 22.2 V. These values are engineering conventions and should not replace the exact manufacturer's specification. Some modern commercial intelligent batteries use slightly different nominal values because their cell chemistry and operating windows differ from the conventional 3.7/4.2 V model.

DJI's official specifications provide useful real-world examples. The Mini 3 Intelligent Flight Battery is specified as Li-ion with a nominal voltage of 7.38 V and a maximum charging voltage of 8.5 V. The Air 3 battery is specified as a LiPo 4S battery with a nominal voltage of 14.76 V and a maximum charging voltage of 17 V. The Mavic 3 battery is specified as LiPo 4S with 15.4 V nominal voltage and a 17.6 V charging voltage limit. The Matrice 4 Series battery is specified as Li-ion 4S with 14.76 V standard voltage and 17.0 V maximum charging voltage. These examples show why a database should store exact manufacturer values rather than rounding everything to generic 3.7 V or 14.8 V categories.

Voltage is directly related to power. Electrical power is approximately P = V × I, so a higher voltage can provide a given power level at lower current. For example, if a propulsion system requires 1000 W, a theoretical 10 V system would require about 100 A, while a 20 V system would require about 50 A, ignoring losses. Lower current can reduce resistive losses because wiring and battery losses include an I^2R component. Higher-voltage propulsion systems can therefore be advantageous for larger aircraft, although the complete motor, ESC, battery and wiring system must be designed for the selected voltage. Voltage alone does not determine efficiency because motor and propeller operating points, controller losses and battery internal resistance also matter.

Voltage also changes during a flight. At high state of charge the pack voltage is higher, and under heavy load the terminal voltage can fall because of internal resistance and electrochemical polarization. This voltage sag can become more pronounced as the battery ages because internal resistance may increase. A drone's BMS and flight controller can use voltage, current and other measurements to estimate state of charge and remaining energy. Recent UAV BMS literature identifies SOC, SOH, state of power and state of energy as important battery-state variables. Voltage is therefore not simply a specification printed on the battery; it is also an important real-time indicator of battery condition.

Temperature affects voltage behaviour as well. At low temperature, electrochemical kinetics become slower and internal resistance can increase, producing greater voltage sag under load and reducing available power. This is especially important in aviation because a battery that appears adequately charged at rest may experience a substantial voltage drop during a high-power manoeuvre. At high temperature, electrochemical reactions and degradation processes can accelerate, and safety risks increase if operating limits are exceeded. UAV battery research therefore treats voltage together with current and temperature rather than as an isolated variable.

For compatibility assessment, voltage must be checked before capacity. A battery with the wrong voltage can damage electronics, produce inadequate motor performance or trigger protective shutdown. However, matching voltage is still not sufficient for compatibility. Connector type, physical dimensions, BMS communication, maximum current, weight and firmware requirements must also match the aircraft. Manufacturers commonly specify dedicated intelligent batteries for their aircraft, and some batteries communicate with the aircraft to report battery status. The database should therefore include nominal voltage, maximum charge voltage, cell count, chemistry, voltage measurement range if available and compatible aircraft models.

The recommended database format is to record voltage as “nominal voltage / maximum charging voltage / cell configuration.” For example, “14.76 V / 17.0 V / Li-ion 4S” is much more informative than simply “14.8 V.” Research and manufacturer documentation support this approach because battery voltage changes with operating conditions and because different commercial packs use slightly different voltage windows. The most authoritative value for a particular commercial battery is the current manufacturer specification, while peer-reviewed research should be used to explain the electrical principles and behaviour. This combination provides a reliable and auditable voltage field for a drone-battery database.

References: DJI official technical specifications for Mini 3, Air 3, Mavic 3 and Matrice 4 Series batteries. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. UAV battery and avionics reviews published in Applied Sciences and related peer-reviewed journals.

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Capacity

Capacity

Battery capacity describes the quantity of electrical charge that a battery can deliver under specified test conditions. It is normally expressed in milliampere-hours (mAh) or ampere-hours (Ah). One ampere-hour is equal to 1000 milliampere-hours, so a 5000 mAh battery has a nominal charge capacity of 5 Ah. Capacity is an important parameter for drone batteries because it influences how long the aircraft can operate, but it should never be interpreted as a direct measure of flight time. Actual endurance depends on battery voltage, energy, aircraft power consumption, battery mass, payload, aerodynamic efficiency, temperature, wind, flight mode and the reserve maintained for safe landing.

The relationship between charge capacity and energy is particularly important. Approximate battery energy can be calculated from nominal voltage and ampere-hour capacity using E(Wh) ≈ V × Ah. For example, a 15.4 V battery with 5 Ah capacity has approximately 77 Wh of nominal energy. DJI's official Mavic 3 specification gives 5000 mAh capacity, 15.4 V nominal voltage and 77 Wh energy, illustrating the relationship. The calculation is an approximation because battery voltage varies during discharge, but nominal voltage multiplied by rated capacity is a useful standardized way to compare batteries. Commercial drone batteries demonstrate wide capacity ranges. For the Air 3, DJI specifies 4241 mAh and 62.6 Wh. For the Mavic 3, the specified capacity is 5000 mAh and energy is 77 Wh. The Matrice 4 Series uses a 6741 mAh Li-ion 4S battery with 99.5 Wh energy. These values are manufacturer specifications and should be treated as model-specific data rather than universal values for a drone class.

A major reason capacity cannot be equated with flight time is the mass of the battery itself. Increasing capacity usually requires more active material and therefore more battery mass. A heavier aircraft requires additional thrust, and additional thrust requires additional electrical power. The benefit of extra stored energy can therefore be partly offset by the increased energy required to carry the battery. Research reviews of UAV power systems identify this mass-energy trade-off as a central reason why battery-powered drones have limited endurance. The optimal battery is not necessarily the one with the largest mAh rating; it is the one that provides the required energy and power within the aircraft's weight and propulsion constraints.

Capacity is also affected by discharge conditions. A battery may deliver a different usable capacity at high current than under a low-current laboratory discharge. Temperature can also change the available capacity, particularly at low temperatures. Aging reduces capacity through electrochemical degradation, so a battery rated at 5000 mAh when new may deliver substantially less after many cycles or prolonged calendar aging. Recent research on UAV battery reliability emphasizes state of health, which can be expressed approximately as the ratio between current available capacity and nominal capacity. A battery-management system can estimate this parameter using voltage, current, temperature and historical data.

The rated capacity should be copied directly from the manufacturer's documentation. If experimental measurements are available, they should be recorded separately with the test temperature, discharge rate, cut-off voltage and measurement method. This distinction is essential because two measurements of the same battery can produce different capacities if the test protocols differ. A capacity value without test conditions has limited scientific meaning.

The database should also record energy in watt-hours because Wh allows batteries with different voltages to be compared more appropriately than mAh. For example, a 4000 mAh battery at 7.4 V contains approximately 29.6 Wh, while a 4000 mAh battery at 14.8 V contains approximately 59.2 Wh. The two batteries have the same charge capacity in mAh but very different stored energy. Therefore, a professional drone-battery database should include mAh, Ah, nominal voltage and Wh rather than using capacity alone.

Capacity should be connected to operational planning. The usable energy is normally less than the theoretical nominal energy because safe operation requires a reserve, and high-current flight can increase losses. Wind, payload and manoeuvring further change power demand. Research on UAV endurance repeatedly emphasizes that energy density, aircraft efficiency and mission profile jointly determine endurance. Consequently, the best practice is to report capacity as a precise battery specification and flight time as a separate, condition-dependent performance parameter. This approach keeps the database technically accurate and prevents the common mistake of assuming that higher mAh automatically means proportionally longer flight.

References: Thermal Science and Engineering Progress 38, 101677. Unmanned Aerial Vehicle Technologies, Applications, and Regulatory Frameworks: A Scoping Review (2026), Drones. Power Sources for Unmanned Aerial Vehicles: A State-of-the Art (2023), Applied Sciences.

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Charging Time

Charging Time

Charging time is the period required to restore a drone battery from a specified starting state of charge to a specified final state of charge under a defined charging system. It is not a fixed chemical property of the battery

because it depends on capacity, charger power, charging current, temperature, battery-management controls, initial state of charge, charging hub configuration and the manufacturer's charging algorithm. For a scientifically useful database, charging time must therefore be recorded together with the charger and charging method. A statement such as “one hour” is incomplete unless the starting condition and charger are known.

Most rechargeable lithium batteries use a controlled constant-current/constant-voltage charging process. During the constant-current phase, the charger supplies controlled current while battery voltage rises. When the specified voltage limit is reached, the system transitions to a constant-voltage phase and current gradually decreases. The final part of charging can therefore take a disproportionate amount of the total time. Intelligent drone batteries may add temperature limits, cell balancing and communication between the battery and charger. These controls are important because fast charging increases heat generation and can accelerate degradation if performed outside the manufacturer's approved operating envelope.

Commercial DJI batteries illustrate the importance of charging method. DJI specifies that the Mini 3 standard battery takes approximately 64 minutes when charged in the aircraft using a DJI 30 W USB-C charger and approximately 56 minutes when inserted in the Two-Way Charging Hub using the same charger. The Intelligent Flight Battery Plus takes approximately 101 minutes in the aircraft and 78 minutes in the charging hub. These differences show that the charging interface and thermal environment can change the charging time even when the battery itself is unchanged. DJI also specifies a charging temperature range of 5°C to 40°C for these batteries.

For the Air 3, DJI specifies approximately 80 minutes with the 65 W Portable Charger and approximately 60 minutes with the 100 W USB-C Power Adapter and Battery Charging Hub. The Air 3 charging hub can charge three batteries sequentially. The Matrice 4 Series uses a 100 W power adapter and a charging hub capable of charging four batteries sequentially, with a standard mode targeting 100% state of charge and a standby mode targeting 90%. These manufacturer-defined charging options demonstrate that “charging time” should be stored as multiple records when a battery supports more than one approved charging method.

Charging temperature is a critical control parameter. Charging lithium batteries outside the approved temperature range can increase degradation and safety risk. DJI commonly specifies 5°C to 40°C as the battery charging range for the commercial models considered here. In cold conditions, the battery may need to warm before charging, while after a high-power flight the battery may be too hot to charge immediately. The correct procedure is to follow the manufacturer's battery-management system and operating instructions rather than forcing the charging process. Research on UAV battery systems also identifies temperature monitoring, charging control and state estimation as important parts of the battery-management system.

Fast charging is attractive for drone operations because it reduces turnaround time, especially for commercial fleets. However, research on lithium batteries for UAV applications warns that very rapid charging can increase battery stress and may accelerate aging. The trade-off involves mission availability, charging time, heat generation and long-term cycle life. A fleet operator may therefore prefer a controlled charging strategy that provides adequate turnaround without maximizing charging rate at every opportunity. For a research database, maximum charging power and manufacturer-approved charging time should be recorded separately so that fast-charging capability is not confused with recommended routine charging practice.

Charging time also depends on the starting state of charge. A battery charged from 20% to 80% will generally require much less time than one charged from near zero to 100%, and the final portion of a full charge may be slower because the charger enters the constant-voltage phase. Consequently, the database should ideally contain “manufacturer full-charge time,” “partial-charge time” when available, charger power and charging temperature. If an experimental charging time is measured, the starting SOC, ending SOC, ambient temperature, charger rating and battery condition should be recorded.

Safe charging requires the use of an approved charger or charging system, a non-damaged battery and suitable ventilation. Batteries showing swelling, leakage, physical damage, abnormal smell or unusual heating should not be charged. FAA guidance specifically warns that damaged lithium batteries may create dangerous heat or sparks and should not be carried by air unless made safe. For transport, lithium battery types are also subject to UN 38.3 testing requirements. These rules are separate from everyday charging but demonstrate why battery charging must be treated as a safety-critical activity.

The most reliable database entry therefore contains the battery model, charger model, charging power, charging method, starting SOC, ending SOC, charging temperature and manufacturer-reported time. Research findings should be used to explain the mechanisms behind charging behaviour, while exact times for commercial batteries should come from the manufacturer. This combination provides a reproducible and defensible charging-time record and avoids presenting a single approximate number as universally valid.

References:. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. FAA PackSafe lithium-battery guidance. UNECE Manual of Tests and Criteria, Section 38.3.

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Flight Time

Approximate Flight Time

Flight time is the duration for which a drone can remain airborne using a specified battery under defined conditions. It is one of the most visible battery-performance measures, but it is also one of the easiest parameters to misinterpret. A manufacturer's maximum flight-time figure is normally obtained under controlled test conditions and may involve a specific speed, payload, wind condition, camera configuration, altitude and battery depletion criterion. Real operational flight time is usually lower because pilots must maintain a safety reserve and because wind, temperature, payload, manoeuvring and battery aging change energy consumption. For a research database, manufacturer-rated maximum flight time and realistic operational planning time should therefore be treated as separate fields.

The fundamental relationship is between stored usable energy and average electrical power consumption. In simplified form, flight time in hours is approximately usable battery energy in watt-hours divided by average electrical power in watts. For example, a battery with 77 Wh nominal energy supplying an average 150 W electrical load would have a theoretical endurance of approximately 0.51 hours, or about 31 minutes, before considering reserves and losses. This calculation is only an engineering approximation. The aircraft does not necessarily consume constant power, and the available battery energy depends on current, temperature, battery condition and the allowable voltage range.

Battery energy density is a major limitation on UAV endurance. Peer-reviewed UAV reviews identify battery energy density and battery mass as central constraints because the battery itself contributes significantly to aircraft weight. Increasing battery capacity can add energy but also adds mass, which increases the thrust required by a multirotor. Propeller size, motor efficiency, aerodynamic design and flight mode therefore interact with battery selection. For multirotors, hovering can be particularly energy intensive because the aircraft continuously generates thrust to counter gravity, while efficient forward flight can sometimes require less power than stationary hover depending on aircraft design and speed.

DJI's Mini 3 provides a clear example of condition-dependent flight time. DJI specifies a maximum flight time of 38 minutes with the standard 2453 mAh battery and 51 minutes with the 3850 mAh Intelligent Flight Battery Plus. The stated maximum is measured in a controlled environment with the aircraft flying forward at 21.6 km/h until forced landing due to battery depletion. DJI also specifies maximum hovering times of 33 and 44 minutes for the two batteries under controlled laboratory conditions. These values are not contradictory; they represent different test conditions and demonstrate why a database should retain the manufacturer's test description along with the flight-time number.

Operational conditions can substantially reduce endurance. Wind increases the aerodynamic power required to maintain a desired ground track. High-speed manoeuvres increase propulsion demand, and repeated acceleration requires additional power. Payload increases aircraft mass, while cold temperatures can reduce battery performance and increase voltage sag. Battery aging can also increase internal resistance and reduce available capacity. Recent UAV battery reliability research emphasizes state of charge, state of health, state of power and state of energy because a battery's remaining percentage alone does not fully describe how much useful energy or power is available.

Altitude and temperature are also relevant. Lower air density at altitude changes propeller thrust generation and can affect propulsion efficiency. Low temperature can increase battery resistance and reduce available power, while high temperature can increase degradation and safety risk. A recent review of battery

management in electric aviation also notes that low and fluctuating temperatures can reduce lithium-ion battery performance. These environmental effects mean that flight-time estimates should be accompanied by operating conditions whenever possible.

For professional mission planning, the correct value is not the maximum time until forced landing. A safety reserve should be retained to allow the aircraft to land or execute a return-to-home procedure. The exact reserve should follow the aircraft manufacturer's operating guidance and the applicable operational rules. The database can therefore contain three related fields: manufacturer maximum flight time, manufacturer maximum hover time, and operational planning time. The third value should be labelled as an estimate rather than a universal specification unless it is supported by a defined test protocol.

Battery health should also be incorporated into flight-time predictions. A new battery may achieve the manufacturer's test performance, while an aged battery with reduced capacity and increased internal resistance may provide less endurance. Research on drone battery cycle life demonstrates the value of collecting realistic flight-profile cycle data and estimating state of health. For a fleet database, battery ID, cycle count, SOH, measured capacity and historical flight duration can be linked to improve predictive maintenance and mission planning.

The recommended conclusion for a drone-battery database is that flight time is a system-level performance parameter rather than a battery-only specification. The battery supplies energy, but the aircraft determines how rapidly that energy is consumed. The most accurate record therefore combines battery Wh, battery mass, aircraft model, payload, manufacturer-rated flight time, test conditions, measured operational time and remaining reserve. This method is consistent with research literature and prevents the common mistake of treating advertised flight time as a guaranteed field performance value.

References: DJI Mini 3 official specifications. Unmanned Aerial Vehicle Technologies, Applications, and Regulatory Frameworks: A Scoping Review (2026), Drones. Xiao et al. (2023), Thermal Science and Engineering Progress 38, 101677. Battery cycle life assessment for a lift+cruise electric VTOL transporter drone (2023).

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Cycle Life

Cycle Life

Cycle life describes how many charge-discharge cycles a battery can complete before reaching a defined end-of-life condition. It is an essential parameter for drone fleet economics and maintenance because battery replacement is a recurring cost and because degraded batteries can reduce flight endurance and power capability. However, cycle life is not a universal number for a battery chemistry. It depends on the cell design, depth of discharge, charge rate, discharge rate, temperature, storage condition, voltage limits, mechanical stress and the end-of-life criterion used by the test. A technically correct database must therefore record both the cycle count and the conditions under which that cycle count was obtained.

A full cycle can be understood as cumulative energy throughput equivalent to one complete charge-discharge cycle. If a battery is discharged from 100% to 50% and later from 50% to 0%, the two partial events together approximate one full discharge cycle, although real battery-management systems may calculate cycle count using their own algorithms. This distinction matters because drone operators often perform short flights and recharge batteries before they are empty. The battery can accumulate substantial equivalent full cycles even when no individual flight represents a complete discharge.

Battery aging generally appears as capacity fade and increasing internal resistance. Capacity fade reduces the amount of energy available, while resistance growth can increase voltage sag and heat generation during high-current operation. A battery can therefore become unsuitable for demanding drone missions before its measured capacity has fallen to a very low value. Research on UAV battery reliability emphasizes state of health, state of power and remaining useful life rather than relying on cycle count alone. State of health can be expressed approximately as current usable capacity divided by rated capacity, although more complete health assessment can include resistance, power capability and other indicators.

The literature also demonstrates why realistic flight-profile testing is important. A 2023 study on cycle-life assessment for a lift-plus-cruise transporter drone used experimental battery cycling based on realistic

operating profiles to estimate state of health and cycle life. Such studies are more informative for UAV applications than generic laboratory cycle-life claims because UAV batteries experience dynamic loads rather than constant-current discharge. Take-off, climbing, cruise, hovering, payload operation and landing can all produce different current and temperature histories.

Manufacturer specifications may provide a cycle-count limit for a particular intelligent battery. DJI, for example, specifies a cycle count of 200 for the Matrice 4 Series Intelligent Flight Battery. This number should be recorded as a manufacturer specification for that specific battery rather than generalized to all Li-ion or drone batteries. DJI's technical documentation also specifies the battery chemistry, energy, temperature range and charging characteristics, which helps place the cycle count in context. Other batteries may have different cycle specifications or may not publish a single guaranteed cycle number.

Temperature is one of the major variables affecting degradation. High temperatures accelerate unwanted chemical reactions and can increase aging, while very low temperatures can increase resistance and reduce available power. Charging at high rates can also increase stress and heat. Deep discharge may increase degradation compared with more moderate depth-of-discharge operation. Storage at high state of charge and high temperature can contribute to calendar aging even when the battery is not being flown. Consequently, cycle life is best understood as the result of both cycling stress and calendar aging.

For fleet management, a cycle counter should be combined with battery capacity measurements, internal resistance or equivalent health indicators, temperature history and abnormal-event records. A battery that has completed fewer cycles but has experienced severe overheating or physical damage may be less suitable for flight than a battery with more cycles that has been operated under controlled conditions. Conversely, a battery with a high cycle count but excellent health data should still be evaluated according to the manufacturer's replacement guidance. The decision should be conservative because battery failure in flight can have consequences beyond the cost of the battery.

Remaining useful life is a research area of growing importance. UAV battery-management systems can estimate RUL using mathematical models, equivalent-circuit models, machine-learning methods or hybrid approaches. Recent reviews describe SOC, SOH, state of power, state of energy and RUL as complementary state variables. RUL is normally expressed as the remaining number of cycles before a defined end-of-life threshold. A common research convention uses 80% of initial capacity as an end-of-life threshold, but this must not be assumed to be the official retirement criterion for every commercial battery.

The recommended database fields are rated cycle life, manufacturer end-of-life criterion, measured cycle count, current SOH, test temperature, charge/discharge rate, depth of discharge, storage history and battery ID. Manufacturer cycle counts should be labelled separately from laboratory or field measurements. If the project performs its own cycle testing, the test protocol should be documented in enough detail for another researcher to reproduce it. This approach makes the database useful for preventive maintenance, predictive maintenance and lifecycle-cost analysis.

The main conclusion is that cycle life is a condition-dependent reliability measure rather than a simple fixed lifespan. A scientifically defensible database should never write “LiPo = X cycles” or “Li-ion = Y cycles” without a defined test protocol. Instead, it should associate every cycle-life value with a specific battery model, operating conditions and end-of-life criterion. This is consistent with current UAV battery research and manufacturer documentation and provides a much stronger basis for battery replacement and safety decisions.

References: Battery cycle life assessment for a lift+cruise electric VTOL transporter drone (2023). DJI Matrice 4 Series official battery specifications. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. Recent lithium-ion degradation research and UAV battery reliability literature.

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Price

Price

Battery price is an economic parameter rather than a fixed technical property, and it changes with manufacturer, model, region, supply availability, battery capacity, integrated electronics, taxes, warranty and seller. For a drone-battery database, price should therefore be recorded as a time-stamped market observation rather than as a permanent specification. A scientifically useful price record should identify the exact battery model, manufacturer, country or market, currency, seller or official source, date checked and whether the product is genuine original equipment, third-party compatible, refurbished or used. Without these fields, two prices cannot be compared reliably.

Original equipment manufacturer batteries are often more expensive than generic cells because a commercial intelligent drone battery may include a complete pack, battery-management electronics, temperature sensing, protection circuits, mechanical housing, communication interfaces and firmware-related functions. The price therefore represents more than the electrochemical cells alone. Intelligent batteries can communicate battery status to the aircraft and charger, monitor cell conditions and support protective functions. Research on UAV battery-management systems identifies monitoring, balancing, charging control, state estimation and fault diagnosis as important functions, all of which can add system complexity and cost.

Battery price should also be evaluated relative to energy rather than only pack capacity. A useful economic indicator is approximate price per watt-hour, calculated as battery price divided by nominal energy. For example, a battery priced at 100 currency units with 50 Wh nominal energy has a simple cost intensity of 2 currency units per Wh. This measure allows different voltage and capacity classes to be compared, although it does not capture battery lifespan, power capability, safety certification, BMS sophistication or compatibility. A battery with a higher purchase price may have a lower lifecycle cost if it provides longer service life and better reliability.

Lifecycle cost is more meaningful for professional UAV operations than purchase price alone. A fleet operator may need to account for acquisition, charging electricity, inspection, maintenance, battery replacement, downtime, storage, transport and disposal or recycling. If a battery lasts for fewer cycles, its cost per flight may be higher even if its initial price is low. Conversely, a premium battery with higher cycle life can reduce replacement frequency. Research on UAV battery reliability increasingly considers economic reliability and lifecycle management alongside technical performance and safety.

The market price of a battery can change rapidly. Manufacturers may discontinue older models, introduce new batteries or change accessory pricing. Regional taxes and import rules can also affect the final price. For this reason, the database should include a “price verified date” and should not present an old price as a current price. If the project is intended for India, prices should be recorded in Indian rupees and should specify whether GST, shipping and import costs are included. If international comparisons are required, the original local currency should be retained and the conversion date documented.

A further complication is the difference between official and unofficial sellers. Third-party batteries may be less expensive but may not provide the same cell quality, BMS communication, thermal protection or warranty as an OEM battery. Manufacturer guidance may explicitly restrict the use of non-approved batteries. For safety-critical research, the database should therefore separate OEM batteries from aftermarket alternatives rather than ranking them solely by price. A low-cost battery should not be treated as equivalent to a certified or manufacturer-approved battery simply because voltage and capacity appear similar.

Current manufacturer documentation also demonstrates that battery price information may be distributed separately from technical specifications. DJI, for example, provides detailed battery specifications and maintains separate accessory-price information for some products and regions. This supports the practice of keeping technical specifications and market-price observations in separate database fields. When a current official price is unavailable, the correct entry is “price not verified” rather than an invented estimate. Historical prices can still be useful if they are clearly labelled by date and market.

For research analysis, price should be linked with performance parameters. Useful derived indicators include price per Wh, price per rated cycle, estimated cost per flight, and lifecycle cost per delivered Wh. The last measure is particularly informative because a battery that initially costs more may deliver more energy over its service life. However, such calculations require a defined cycle-life assumption and should not be presented as measured fact unless the necessary data are available. Sensitivity analysis can be used to show how conclusions change if cycle life or usable capacity varies.

A professional database entry for price should therefore contain battery model, manufacturer, chemistry, nominal energy, price, currency, country, seller, product condition, date verified, warranty information if available and source type. The price field should be updated periodically because market values change. For academic work, it is preferable to cite the official manufacturer store or official regional price documentation where available and to identify third-party market observations separately.

The main conclusion is that battery price cannot be treated as a single universal number. It is a dynamic market variable that should be time-stamped and normalized for energy and lifecycle when comparisons are required. Combining manufacturer specifications, peer-reviewed lifecycle research and clearly documented market observations provides the most reliable basis for economic analysis of drone batteries.

References: DJI official technical specifications and accessory-price documentation. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. FAA and UNECE guidance for lithium-battery handling and transport, relevant to lifecycle cost and logistics.

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Compatible Drones

Compatible Drones

Battery compatibility means that a particular battery can be safely and correctly used with a specified aircraft model. Compatibility is much more than matching voltage and capacity. A drone battery must fit physically, provide the correct electrical voltage and current, communicate correctly with the aircraft when required, meet the aircraft's weight and balance requirements, use the correct connector or mechanical interface and comply with the manufacturer's firmware and protection requirements. For this reason, compatibility should be treated as a model-specific field in a technical database.

Electrical compatibility begins with voltage. A battery with an incorrect voltage can cause inadequate propulsion performance, controller faults or damage to electronic components. Capacity affects stored energy and mass, while discharge capability determines whether the battery can supply the peak current required during take-off and manoeuvres. However, even a battery with matching voltage, capacity and discharge rating may still be incompatible if the aircraft expects a particular communication protocol or battery-management system. Modern intelligent drone batteries can report temperature, voltage, current, state of charge and fault information to the aircraft.

Physical compatibility is equally important. The battery must fit inside the designated compartment and must be securely retained during vibration and manoeuvring. Its dimensions, mass and locking mechanism must match the aircraft. Connectors must have the correct geometry and current rating. A physically modified battery can introduce risks even if it can be made to fit. For professional applications, battery modifications should not be assumed safe unless they are specifically approved and validated by the manufacturer or an appropriate engineering authority.

DJI's commercial specifications illustrate model-specific compatibility. The Mini 3 uses the Intelligent Flight Battery and Intelligent Flight Battery Plus, with the manufacturer listing the corresponding batteries and charging systems. The Air 3 uses the Air 3 Intelligent Flight Battery and its dedicated charging hub. The Matrice 4 Series documentation identifies the Intelligent Flight Battery as compatible with the Matrice 4E/T Series. DJI also publishes charging-hub compatibility information showing which battery families can be charged by particular hubs. These manufacturer records are more authoritative than third-party claims because they account for both physical and electronic compatibility.

Battery compatibility can also be affected by regional product variants. Some battery versions may have different capacities or regulatory constraints in particular markets. The Mini 3 is a good example because the standard and Plus batteries have different masses and capacities, and DJI notes that the Plus version may not be sold in every region. A database should therefore record region-specific availability and not assume that every battery option is globally available.

Weight is an important compatibility consideration because adding a higher-capacity battery may increase aircraft mass. For a lightweight drone, crossing a regulatory mass threshold can also affect the aircraft's legal or operational classification in some jurisdictions. Even where no regulatory threshold is crossed, additional

mass changes propulsion requirements and can alter flight performance. DJI's Mini 3 documentation explicitly notes that using the Battery Plus increases aircraft weight and can affect propulsion. Therefore, compatibility should include both “physically/electronically compatible” and “performance/regulatory implications” where relevant.

Research on UAV batteries emphasizes the importance of system-level integration. Battery-management systems are responsible for monitoring and protection, while cell balancing and state estimation support reliable operation. If an aircraft cannot communicate with a substitute battery or cannot correctly estimate its state of charge, the apparent compatibility may be misleading. A battery may power the motors temporarily but still be unsuitable for operational use because the aircraft's safety systems cannot validate battery condition.

The recommended database structure is to store compatible aircraft by exact model and, when necessary, model variant. For example, “DJI Matrice 4E/T Series” is more useful than “DJI enterprise drones.” Each entry should also include the manufacturer's compatibility statement, battery part number, charger compatibility, region and any restrictions. If a third-party battery is being evaluated experimentally, it should be labelled “tested compatibility” rather than “manufacturer-approved compatibility” unless official documentation supports the latter.

Compatibility should also be periodically revalidated because firmware updates, product revisions and battery revisions can change system behaviour. A battery that was compatible with an earlier aircraft revision may not necessarily be approved for a later platform. The database should therefore include a source date and last-verified date. If compatibility is uncertain, the safest classification is “not verified” rather than “compatible.”

The overall conclusion is that battery compatibility is a multi-parameter engineering relationship between battery and aircraft. Voltage and capacity are necessary checks but are not sufficient. Physical fit, connector, current capability, BMS communication, firmware, mass and manufacturer approval must also be considered. For an authenticated drone-battery database, exact manufacturer compatibility statements should be the primary evidence, while research papers should be used to explain why these compatibility factors affect flight safety and performance.

References: DJI official specifications and support documentation for Mini 3, Air 3 and Matrice 4 Series. DJI Battery Charging Guide and Intelligent Flight Battery Technical Specifications.. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. Xiao et al. (2023), Thermal Science and Engineering Progress 38, 101677.

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Manufacturer

Manufacturer

The manufacturer field identifies the organization responsible for producing or supplying the drone battery pack and should be treated as an essential identity field in a technical database. A modern drone battery may involve several organizations: the drone manufacturer, the battery-pack manufacturer, the cell manufacturer, the battery-management electronics supplier and the final brand or distributor. These roles should not be confused. For example, a drone brand may design the aircraft and battery system while sourcing individual cells from another company. The battery model or part number is therefore as important as the brand name when identifying a specific product.

For commercial drone batteries, the manufacturer provides the most authoritative information for model-specific specifications such as capacity, nominal voltage, charging voltage, charging temperature, maximum charging power, weight, chemistry and compatible aircraft. DJI is an example of a manufacturer that publishes detailed Intelligent Flight Battery specifications for multiple aircraft families. Its documentation lists the Mini 3 battery as Li-ion with 2453 mAh capacity and 7.38 V nominal voltage, the Air 3 battery as LiPo 4S with 4241 mAh and 14.76 V, the Mavic 3 battery as LiPo 4S with 5000 mAh and 15.4 V, and the Matrice 4 Series battery as Li-ion 4S with 6741 mAh and 14.76 V.

Manufacturer information is particularly important because drone batteries can contain proprietary electronics. An intelligent battery can include a microcontroller, memory, temperature sensors, current sensing, cell-voltage monitoring, protection circuits and communication functions. The aircraft may use these data to determine whether the battery is safe for flight and to estimate remaining energy. Consequently, replacing an OEM battery with a visually similar third-party pack can change system behaviour even when the cell chemistry and capacity appear similar.

For research databases, manufacturer identity should be recorded using a hierarchy. The first field should be “battery brand/manufacturer,” followed by “battery model/part number.” A separate field can identify “drone manufacturer,” and another can identify “cell manufacturer” if verified. A fourth field can identify “source of specification,” such as official technical manual, official product page or official support document. This structure prevents confusion when a drone brand and battery cell supplier are different organizations.

The manufacturer also establishes important operating limits. These can include charging temperature, operating temperature, maximum charging power, discharge rate, storage recommendations and replacement criteria. Such limits should not be replaced by generic values from unrelated batteries. Lithium-ion and lithium-polymer batteries can differ significantly, and even two batteries using the same chemistry can have different safe operating envelopes because of cell design, pack construction and BMS configuration.

A strong database should therefore distinguish “manufacturer-verified” data from “research-derived” data. Manufacturer values should be cited for exact product specifications, while research citations should support general scientific interpretation. Manufacturer information also changes over time. Product revisions, firmware updates, regional versions and discontinued batteries can create differences between older and newer documents. The database should therefore record the publication or access date and retain the exact model identifier. When a battery is discontinued, the historical record can remain valuable, but the database should identify it as discontinued rather than presenting it as a current product.

Warranty and service information may also be useful. Battery replacement programs, warranty periods, repairability and recycling arrangements affect lifecycle cost and operational planning. However, warranty conditions are commercial terms and should be stored separately from technical performance data. A manufacturer warranty should never be interpreted as a guarantee of a specific number of cycles or flight minutes unless the warranty explicitly states such a condition.

The manufacturer field can also support authentication. An authenticated database should prioritize manufacturer websites, technical manuals, service documents and official regional stores. If a specification appears only on a marketplace listing or social-media post, it should be treated as secondary evidence until confirmed by the manufacturer. This is especially important for batteries because counterfeit or modified packs may have inaccurate capacity labels, inferior cells or inadequate protection circuitry. The recommended manufacturer record therefore includes manufacturer name, battery model, part number, chemistry, manufacturing or revision information when available, official specification source, compatible aircraft, official charger, warranty information, region, date verified and status. If cell manufacturer information is unavailable from authoritative sources, the database should state “not publicly verified” rather than guessing from photographs or online claims. This approach preserves scientific integrity and makes every battery entry traceable to an authoritative source.

References: DJI Intelligent Flight Battery Technical Specifications and official aircraft support pages. Zhao et al. (2025), Drones 9(8), 539. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. Xiao et al. (2023), Thermal Science and Engineering Progress 38, 101677. FAA lithium-battery safety guidance. UNECE Manual of Tests and Criteria, Section 38.3.

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Maintenance

Maintenance Requirements

Drone battery maintenance is the set of inspection, charging, storage, monitoring and lifecycle-management practices used to keep a battery safe and serviceable. Battery maintenance is especially important for UAVs because the battery is a flight-critical component and failure can result in loss of propulsion and aircraft

control. Maintenance should therefore be treated as a preventive safety activity rather than simply a method of extending battery life. The exact procedures must follow the battery and aircraft manufacturer's instructions, while research literature provides the scientific basis for understanding degradation and failure mechanisms.

Visual inspection should be performed before flight and after abnormal events. The battery should be checked for swelling, deformation, cracks, damaged connectors, corrosion, leakage, burn marks, unusual odour and other physical abnormalities. A battery that has been severely impacted, crushed, punctured, exposed to water contrary to its rating or otherwise damaged should not be returned to service merely because it still powers the aircraft. FAA guidance for lithium batteries warns that damaged or recalled batteries capable of generating dangerous heat or sparks present a safety risk. Older drone battery guidance also specifically warns against using or charging batteries that are swollen, leaking or damaged.

Temperature management is a major maintenance requirement. Lithium batteries should be charged only within the manufacturer's specified charging-temperature range. DJI specifies 5°C to 40°C for several of its intelligent flight batteries, including the Mini 3, Air 3 and Matrice 4 Series. After a demanding flight, the battery may be warm and should be allowed to return to an acceptable temperature before charging if the manufacturer requires this. Batteries should also be protected from direct sunlight and excessive heat during storage and transport. Low temperature can reduce available power and increase voltage sag, while high temperature can accelerate degradation and increase safety risk.

Charging maintenance involves using the correct charger, charging hub and approved battery-management system. Batteries should not be charged unattended in inappropriate locations, and damaged batteries should never be forced to accept charge. The charging system should be kept clean and dry, connectors should be inspected for contamination or damage, and cables should not be used if damaged. Intelligent batteries may automatically manage cell balancing and charging cut-off, but the operator remains responsible for inspecting the battery and following the manufacturer's procedures.

Storage is another important part of maintenance. Lithium batteries generally age through both cycling and calendar aging. Keeping a battery at very high state of charge for prolonged periods can increase stress, particularly at elevated temperature. Some intelligent drone batteries automatically reduce their state of charge after a period of inactivity. The operator should follow the manufacturer's recommended storage condition rather than applying a generic rule to every battery. A storage record can include date stored, approximate SOC, storage temperature and date of next inspection. Battery history should be recorded for professional operations. A useful maintenance log includes battery ID, model, purchase date, cycle count, last flight date, charging events, abnormal temperature events, measured capacity if available, SOH estimate, physical inspection results and service status. This allows a fleet manager to identify batteries that are deteriorating faster than others. Research on UAV battery reliability emphasizes state estimation and predictive maintenance because cycle count alone does not fully represent battery health.

Cell balance is particularly important for multi-cell packs. Manufacturing variation, temperature gradients and aging can cause individual cells to diverge in voltage and capacity. If cell imbalance becomes significant, one cell may reach a voltage limit earlier than the others, reducing usable pack capacity and increasing risk during charging or discharge. Battery-management systems use balancing and protection strategies to reduce these problems. Maintenance records should therefore include cell-voltage imbalance or battery-reported cell condition when the aircraft or battery provides that information.

A battery should be retired when it meets the manufacturer's retirement criteria, develops physical damage or exhibits unsafe or abnormal behaviour. Research may use an 80% capacity threshold as a conventional end-of-life definition, but this should not automatically become the operational retirement rule for a particular drone. Manufacturers may set different criteria based on their battery design and BMS. For safety-critical applications, operators may also adopt conservative internal thresholds for capacity, resistance, swelling or abnormal temperature.

End-of-life batteries require controlled disposal or recycling. Lithium batteries should not be thrown into ordinary waste because damaged cells can create fires during handling and waste processing. The appropriate method is to follow local hazardous-waste or battery-recycling requirements and the manufacturer's instructions. During transport, lithium batteries may also be regulated as dangerous goods. UNECE UN 38.3 establishes testing requirements for lithium cells and batteries intended for transport, while FAA guidance

addresses transport risks for lithium batteries in aviation. The best maintenance system combines physical inspection, correct charging, temperature control, appropriate storage, battery-history logging, health monitoring and controlled retirement. Research literature supports this lifecycle approach because degradation is influenced by operating conditions rather than cycle count alone. A professional database should therefore contain maintenance status, last inspection date, abnormal-event history, current SOH, cycle count, storage condition and retirement reason. This transforms the battery database into a practical maintenance and safety-management tool.

References: FAA PackSafe – Lithium Batteries and PackSafe – Drones/UAS. DJI official Intelligent Flight Battery specifications and charging guidance. Zhao et al. (2025), Drones 9(8), 539. A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs (2023), IEEE Access. UNECE Manual of Tests and Criteria, Section 38.3. NASA lithium-battery thermal-safety research.

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Safety Information

Safety Information

Drone battery safety is primarily concerned with preventing electrical, thermal and mechanical failure and with controlling the consequences if a battery becomes damaged. Lithium-ion and lithium-polymer batteries contain substantial electrochemical energy in a compact package, which is a major reason they are valuable for UAVs but also why misuse can produce severe hazards. Research and government guidance identify overcharge, over-discharge, short circuit, mechanical damage, excessive temperature and manufacturing defects as important contributors to lithium-battery failure. For drones, safety is particularly important because a battery failure during flight can cause loss of propulsion and aircraft control in addition to creating a fire hazard.

Thermal runaway is one of the most serious battery failure mechanisms. It is a self-accelerating process in which internal heat generation exceeds the ability of the cell to dissipate heat, causing temperature to rise rapidly and triggering further exothermic reactions. A damaged or electrically abused cell can enter thermal runaway, producing high temperatures and potentially releasing gases and other battery materials. NASA technical research on lithium-ion cells emphasizes that thermal runaway can propagate from one failed cell to neighbouring cells within a battery pack. This is why pack design, cell spacing, thermal management, sensors and protective controls are important in aviation applications.

Overcharging is a major electrical hazard because the cell is forced beyond its intended voltage range. Proper battery-management and charging systems are designed to prevent this condition. Over-discharge can also damage cells and reduce reliability. External short circuits can create very high current and rapid heating, while internal short circuits can occur after mechanical damage or internal defects. A battery should therefore never be punctured, crushed, bent, opened or modified. Older FAA drone battery safety guidance explicitly warns against altering, puncturing, throwing, bending or impacting lithium-polymer batteries and advises users not to use or charge swollen, leaking or damaged batteries.

Temperature is a critical safety variable. Excessive heat can accelerate degradation and increase the probability of thermal events. Batteries should not be left in hot vehicles, exposed to direct intense sunlight or charged outside the manufacturer's temperature limits. Cold conditions can also be hazardous because low temperature increases internal resistance and reduces available power. The correct practice is to follow the manufacturer's operating and charging temperature limits and to use the aircraft's battery-management system where provided. DJI specifications for several current intelligent batteries specify a 5°C to 40°C charging range.

Battery-management systems are a central layer of protection. A modern intelligent UAV battery can measure pack and cell voltage, current and temperature and can estimate state of charge and state of health. It can also control charging, protect against abnormal electrical conditions and communicate battery status to the aircraft. Research on UAV BMS systems identifies charging and discharging control, cell balancing, SOC estimation, SOH estimation, remaining useful life prediction and fault diagnosis as major research areas. These functions are important because a drone experiences dynamic loads and because the pilot needs reliable information about remaining usable energy.

Physical inspection is one of the simplest and most important safety controls. Before flight, the operator should inspect the housing and connectors and check for swelling, cracks, deformation, leakage, corrosion, abnormal smell and signs of overheating. After a crash or hard impact, the battery should be treated as potentially damaged even if no external defect is immediately visible. A damaged lithium battery can pose a delayed hazard because internal damage may produce an internal short circuit later. Batteries showing abnormal behaviour should be isolated and handled according to the manufacturer's and local hazardous-material guidance.

Transport creates additional safety requirements. Lithium batteries can be regulated as dangerous goods for air transport. The FAA states that drones and their batteries may be subject to dangerous-goods requirements when transported on passenger aircraft. The UN Manual of Tests and Criteria, Section 38.3, specifies standardized tests for lithium cells and batteries intended for transport, including mechanical and electrical abuse tests. Compliance with transport requirements does not mean a battery is immune from damage; it means that the battery type has undergone specified tests and that transport packaging and rules can be applied.

Storage safety requires preventing short circuits, physical damage and excessive temperature exposure. Batteries should be stored according to manufacturer instructions in an appropriate location away from easily combustible materials. Terminals should be protected against accidental contact, and batteries should not be stored where they can be crushed or punctured. Operators should maintain an inventory so that damaged or recalled batteries can be identified and removed from service. Battery records should include model, serial or unique ID, cycle count, inspection status and any abnormal event.

Fire response should be handled according to the battery manufacturer's instructions, local emergency procedures and trained fire-safety guidance. A suspected thermal event should not be treated as an ordinary small electrical fault because lithium-battery failure can involve intense heat and propagation. If a battery is smoking, swelling rapidly or showing signs of thermal runaway, people should move away and emergency procedures should be followed. Damaged batteries should not be transported casually in vehicles or aircraft. FAA guidance specifically states that damaged or recalled batteries capable of creating dangerous heat or sparks must not be carried aboard aircraft unless made safe.

The final safety principle is prevention through lifecycle management. Battery safety is strongest when good cells, suitable BMS protection, controlled charging, temperature management, regular inspection, health monitoring, conservative retirement criteria and compliant transport are used together. No single safety feature can eliminate every failure mode. Current UAV research therefore approaches battery safety as a system-level reliability problem involving electrochemistry, thermal behaviour, sensors, BMS algorithms, mechanical design and operational procedures. A high-quality database should capture safety-critical fields such as chemistry, voltage limits, charging temperature, operating temperature, protection features, BMS, inspection status, known hazards, transport classification and source documentation.

References: NASA Technical Reports Server, Predicting Maximum Thermal Response in a Li-ion Cell as a Thermal Runaway Predictor for a UAV Flight. FAA PackSafe – Lithium Batteries and PackSafe – Drones/UAS. UNECE Manual of Tests and Criteria, Revision 8 and subsequent amendments, Section 38.3.

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4. Crop-Wise Drone Spraying Information

crop-wise agricultural drone spraying for rice, wheat, maize, cotton, soybean, groundnut, chickpea, pigeonpea, rapeseed-mustard, sugarcane, potato, tomato, chilli, onion, mango, banana, grapes, pomegranate, citrus and coconut

In this section: 01_Rice, 02_Wheat, 03_Maize, 04_Cotton, 05_Soybean, 06_Groundnut, 07_Chickpea, 08_Pigeonpea, 09_Rapeseed-Mustard, 10_Sugarcane, 11_Potato, 12_Tomato, 13_Chilli, 14_Onion, 15_Mango, 16_Banana, 17_Grapes, 18_Pomegranate, 19_Citrus, 20_Coconut

Rice

• Rice – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states: West Bengal, Uttar Pradesh, Punjab, Odisha, Andhra Pradesh, Telangana, Chhattisgarh, Bihar, Tamil Nadu, Karnataka, Assam and Jharkhand.

Major growing districts: East and West Godavari, Krishna, Guntur/Bapatla and Nellore in Andhra Pradesh; Nalgonda, Suryapet, Karimnagar/Jagtial and Nizamabad in Telangana; Bardhaman, Nadia and Murshidabad in West Bengal; Thanjavur, Tiruvarur and Nagapattinam/Mayiladuthurai in Tamil Nadu; major irrigated belts of Punjab, UP, Odisha and Bihar.

Common pest and disease problems: Brown planthopper, white-backed planthopper, stem borer, gall midge and leaf folder are common insect problems. Bacterial leaf blight, blast, sheath blight, sheath rot and false smut are important diseases. ICAR specifically identifies bacterial leaf blight, gall midge and sheath blight as important constraints in Andhra Pradesh.

Common spraying requirements and products: Protection is stage- and threshold-based. ICAR advisories include active ingredients such as hexaconazole, azoxystrobin combinations, mancozeb and isoprothiolane for relevant disease situations. Insecticides are selected according to the target pest and current label. Integrated management, resistant varieties and water/nutrient management remain important.

Suitable drone application information and spray volume: Drone spraying is suitable for large rice fields because aircraft can avoid trampling wet fields and can apply foliar inputs rapidly. ICAR-NBAIR has demonstrated drone-based biopesticide application in rice. Uniform height, speed, swath and wind limits should be validated. A crop-specific India-wide drone volume was not found in the reviewed authoritative sources.

Number and timing of applications and relevant government/agricultural-university information: Applications should follow scouting and crop stage. Planthopper/stem-borer sprays are normally triggered by surveillance or economic-threshold concepts; fungicides are linked to early disease detection and weather risk. Government sources include ICAR-National Rice Research Institute, ICAR-NRIPM, state agricultural universities and KVKs. ICAR-NRIPM's calculator covers rice.

Sources: Government of India Agricultural Statistics at a Glance 2024; ICAR state/rice advisories; ICAR-NRIPM Insecticide and Fungicide Calculators; ICAR-NBAIR drone demonstrations.

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Wheat

• Wheat – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Uttar Pradesh, Madhya Pradesh, Punjab, Haryana, Rajasthan and Bihar, with important areas in Maharashtra, Gujarat and Uttarakhand.

Major growing districts. Karnal, Hisar and Sirsa in Haryana; Ludhiana, Patiala and Sangrur in Punjab; Kota, Ganganagar and Hanumangarh in Rajasthan; Sehore, Raisen and Ujjain/Indore belts in Madhya Pradesh; Meerut, Muzaffarnagar, Agra and Aligarh belts in Uttar Pradesh; major irrigated districts of Bihar.

Common pest and disease problems. Termites, aphids and caterpillar pests occur. Yellow/stripe rust, brown rust, powdery mildew and Karnal bunt are important diseases. ICAR has documented yellow-rust risk particularly in Punjab, Haryana, J&K, Uttarakhand and adjoining UP under cool, wet conditions.

Common spraying requirements and products. ICAR wheat advisories recommend disease scouting and, for yellow rust, propiconazole 25 EC at 0.1% in the cited advisory. Current product registration and label directions must be checked. Herbicide use is stage-specific and should not be transferred to drones without an approved UAV protocol.

Suitable drone application information and spray volume. Drone foliar application can be useful where wet fields make ground access difficult. Wheat has a comparatively open canopy, but droplet drift and uniformity still depend on flight height, speed, nozzle and weather. No crop-specific authoritative Indian drone water volume was found in the reviewed sources.

Number and timing of applications and relevant government/agricultural-university information. Yellow-rust treatment is triggered by early detection and favourable weather; other fungicide applications are risk-based. Relevant institutions include ICAR-Indian Institute of Wheat and Barley Research/Directorate of Wheat Research, state agricultural universities and KVKs. Research papers on UAV cereal spraying emphasize deposition and drift validation.

Sources: ICAR Directorate of Wheat Research/IIWBR; ICAR Rabi Agro-Advisory; Government of India crop statistics; peer-reviewed UAV pesticide-application research.

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Maize

• Maize – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Karnataka, Madhya Pradesh, Maharashtra, Bihar, Telangana, Andhra Pradesh, Rajasthan and Uttar Pradesh are major regions.

Major growing districts. Davanagere, Haveri, Belagavi, Chitradurga and Tumakuru in Karnataka; Nizamabad, Kamareddy and Karimnagar in Telangana; Guntur/Palnadu and Kurnool belts in Andhra Pradesh; important maize districts of Maharashtra, Bihar and Madhya Pradesh.

Common pest and disease problems. Fall armyworm is a major pest, with stem borer, shoot fly and aphids also occurring. Diseases include downy mildew, turcicum and maydis leaf blights, banded leaf and sheath blight and stalk rots.

Common spraying requirements and products. ICAR's 2025 kharif advisory identifies fall armyworm as prevalent and describes pheromone trapping and stage-specific options including biological and registered insecticide choices. Disease management includes resistant hybrids and seed treatment. Current labels must govern chemical selection.

Suitable drone application information and spray volume. Drone use is promising for foliar insecticide, fungicide and nutrient applications. The whorl is a special challenge because larvae may be protected inside it; therefore, area coverage alone is not sufficient. No universal Indian drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Applications are stage- and scouting-dependent. ICAR-Indian Institute of Maize Research, state universities and KVKs are relevant. UAV research shows that height, speed, droplet spectrum and downwash control deposition; maize-whorl penetration requires field validation.

Sources: ICAR Kharif Agro-Advisories 2025; ICAR maize research; Government of India crop statistics.

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Cotton

- Cotton – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Gujarat, Maharashtra, Telangana, Andhra Pradesh, Karnataka, Madhya Pradesh, Rajasthan, Punjab, Haryana and Tamil Nadu.

Major growing districts. Rajkot, Junagadh and Amreli in Gujarat; Akola, Yavatmal, Amravati and Nagpur in Maharashtra; Adilabad/Nirmal, Warangal and Khammam belts in Telangana; Raichur and Vijayapura in Karnataka; major northern cotton districts of Punjab, Haryana and Rajasthan.

Common pest and disease problems. Pink bollworm, Helicoverpa/bollworms, whitefly, jassid, aphids and tobacco caterpillar are important. Cotton leaf curl virus is especially important in the northern zone.

Common spraying requirements and products. IPM emphasizes scouting, pheromone traps, natural enemies and threshold-based treatment. Registered active ingredients such as emamectin benzoate, chlorantraniliprole, spinosyns and flonicamid may be used for appropriate targets when currently approved. Resistance management is important.

Suitable drone application information and spray volume. Drone spraying can be useful for foliar applications in tall cotton, but canopy penetration and drift are major issues. Pink-bollworm/boll targeting needs validated deposition. No crop-specific authoritative Indian drone volume was found, so the database should mark volume as not reliably established.

Number and timing of applications and relevant government/agricultural-university information. Sprays should be triggered by scouting and pest thresholds, not automatic weekly schedules. ICAR-Central Institute for

Cotton Research is the principal national source; ICAR-NRIPM also provides cotton pesticide-calculator information. Research on UAV cotton spraying emphasizes canopy deposition and drift.

Sources: ICAR-CICR; ICAR-NRIPM; Government of India cotton statistics; ICAR state advisories; peer-reviewed UAV cotton-spraying research.

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Soybean

• Soybean – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Madhya Pradesh, Maharashtra and Rajasthan are dominant, with important production in Karnataka, Telangana, Gujarat and Uttar Pradesh.

Major growing districts. Indore, Ujjain, Dewas, Sehore, Raisen and Vidisha in Madhya Pradesh; Latur, Akola, Washim, Buldhana and Amravati in Maharashtra; Kota/Jhalawar belts in Rajasthan.

Common pest and disease problems. Stem fly, girdle beetle, tobacco caterpillar, semiloopers and defoliators are common. Soybean rust, yellow mosaic, bacterial pustule and charcoal/root diseases occur in different environments.

Common spraying requirements and products. ICAR soybean advisories recommend sanitation, suitable varieties and stage-specific control. Examples include chlorantraniliprole or indoxacarb for defoliators and integrated weed/insect management. Exact product use must follow current label claims.

Suitable drone application information and spray volume. Soybean's relatively low canopy can be treated by UAV for foliar insecticide, fungicide and nutrient applications. Drones may be useful when fields are wet. Uniformity and drift must be checked. No authoritative India-wide drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Applications are concentrated around vegetative growth, flowering and pod formation according to pest/disease risk. ICAR-Indian Institute of Soybean Research, ICAR-NRIPM and KVKs are key sources. Research should be used for deposition and efficacy, not to replace label authorization.

Sources: ICAR-Indian Institute of Soybean Research advisory; ICAR Kharif Agro-Advisories 2025; ICAR-NRIPM; Government crop statistics; peer-reviewed UAV soybean research.

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Groundnut

• Groundnut – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Gujarat, Andhra Pradesh, Tamil Nadu, Karnataka and Rajasthan are major regions; ICAR identifies these as major states for high-oleic groundnut varieties.

Major growing districts. Junagadh, Rajkot and Amreli in Gujarat; Anantapur/Sri Sathya Sai, Kurnool and Kadapa in Andhra Pradesh; major Tamil Nadu groundnut districts; Raichur, Ballari and Chitradurga in Karnataka.

Common pest and disease problems. Leaf miner, tobacco caterpillar, red hairy caterpillar, thrips, aphids and jassids occur. Early/late leaf spot, rust, stem/collar rot and root diseases are important.

Common spraying requirements and products. Management combines seed treatment, sanitation, scouting and targeted foliar sprays. Fungicides such as mancozeb and registered triazole/strobilurin options are used according to local recommendations; insecticides are selected for the target pest. ICAR-NRIPM includes groundnut.

Suitable drone application information and spray volume. Groundnut has a low canopy, so UAV deposition close to the soil must be validated. Drones can provide timely foliar protection over wet fields, but rotor downwash and droplet size strongly affect interception. No reliable crop-specific Indian drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Leaf-spot/rust treatments are disease-risk based; insecticide sprays should follow monitoring. ICAR-Directorate of Groundnut Research, state universities and KVKs are relevant. Research papers should be retained when they report actual UAV height, speed, nozzle and deposition.

Sources: ICAR Directorate of Groundnut Research; ICAR-NRIPM; ICAR Kharif advisories; Government crop statistics.

Source: `06_Groundnut.docx` · Google Drive file id `118EIvHxkOyUWLIeYIFZZavdkPq4CWKDA` · folder “4. Crop wise drone spraying information”

Chickpea

- Chickpea – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Madhya Pradesh, Maharashtra, Rajasthan, Karnataka, Andhra Pradesh, Telangana, Uttar Pradesh and Gujarat.

Major growing districts. Sehore, Vidisha, Raisen and Sagar in Madhya Pradesh; Latur, Akola and Washim in Maharashtra; Kalaburagi, Bidar and Vijayapura in Karnataka; major rabi pulse districts in Rajasthan, Telangana, Andhra Pradesh and Uttar Pradesh.

Common pest and disease problems. Gram pod borer/Helicoverpa is the principal insect pest. Cutworms and aphids can occur. Fusarium wilt, Ascochyta blight, dry root rot and Botrytis gray mould are important diseases in suitable environments.

Common spraying requirements and products. IPM uses resistant/tolerant varieties, pheromone traps, biological control and selective insecticides. ICAR rabi material gives pod-borer and Ascochyta examples, while ICAR-NRIPM includes chickpea in its calculator. Current label registration must be verified.

Suitable drone application information and spray volume. Drone foliar spraying can be useful for pod-borer and foliar disease protection once canopy develops. Because larvae may be protected inside flowers/pods, timing and deposition are critical. No crop-specific authoritative drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Pod-borer applications should follow monitoring and flowering/pod stage. Disease sprays are triggered by symptoms and weather risk. ICAR-Indian Institute of Pulses Research, ICRISAT, state universities and KVKs are key sources.

Sources: ICAR Rabi Agro-Advisory; ICAR-NRIPM; ICRISAT pulse IPM literature; Government crop statistics; peer-reviewed UAV research.

Source: `07_Chickpea.docx` · Google Drive file id `1xlrM0KsSfzSLy2uYmsHsSBocqCXbHdg7` · folder "4. Crop wise drone spraying information"

Pigeonpea

• Pigeonpea – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra, Karnataka, Madhya Pradesh, Telangana, Andhra Pradesh, Gujarat and Uttar Pradesh.

Major growing districts. Kalaburagi, Bidar and Yadgir in Karnataka; Latur, Nanded, Akola and Washim in Maharashtra; Adilabad/Nirmal and other Telangana dryland belts; Kurnool and Prakasam in Andhra Pradesh; suitable districts in Gujarat, MP and UP.

Common pest and disease problems. Helicoverpa, Maruca and pod fly form a major pod-borer complex. Fusarium wilt and sterility mosaic disease are major diseases; Phytophthora stem blight may occur in wetter areas.

Common spraying requirements and products. ICAR emphasizes integrated and bio-intensive IPM. Selective insecticides such as emamectin benzoate, chlorantraniliprole or other currently registered options may be recommended by local advisories. Wilt management relies on resistant varieties and sanitation rather than routine foliar spraying.

Suitable drone application information and spray volume. Because pigeonpea becomes tall and dense, UAV canopy penetration is a major design issue. Drones can be used for foliar insecticide/fungicide applications when validated. No authoritative India-wide drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Pod-borer control is most important around flowering and pod formation and should follow monitoring. ICAR-Indian Institute of Pulses Research, ICRISAT and state universities are relevant. Research should be captured with actual flight parameters where reported.

Sources: ICAR state crop material; ICAR-NRIPM; ICRISAT pigeonpea literature; Government crop statistics; peer-reviewed UAV crop-protection research.

Source: `08_Pigeonpea.docx` · Google Drive file id `1Cj-m6P9QN15Cc-uWI3-hdU5ZZX-TGKGG` · folder "4. Crop wise drone spraying information"

Rapeseed-Mustard

• Rapeseed-Mustard – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade

brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Rajasthan, Uttar Pradesh, Madhya Pradesh, Haryana, Punjab, Gujarat and West Bengal.

Major growing districts. Bharatpur, Alwar, Sri Ganganagar and Hanumangarh in Rajasthan; Hisar, Bhiwani and Rewari in Haryana; Bathinda and Muktsar in Punjab; Agra, Aligarh and Mainpuri in UP; important MP and West Bengal districts.

Common pest and disease problems. Aphids and painted bug are common pests. Alternaria blight, white rust, downy mildew and Sclerotinia can occur. ICAR state advisories identify aphids and Alternaria as major constraints.

Common spraying requirements and products. Management relies on timely sowing, monitoring and targeted insecticide/fungicide use. ICAR advisories have recommended mancozeb in high-disease situations; current label and local university guidance should govern the exact product.

Suitable drone application information and spray volume. Drone foliar application is feasible but lower-canopy deposition and drift must be checked. No crop-specific authoritative Indian drone volume was found. The correct SOP should define litres/ha, droplet spectrum, height, speed and wind limits.

Number and timing of applications and relevant government/agricultural-university information. Aphid treatment is linked to population build-up, especially around flowering; disease sprays depend on symptoms/ weather. ICAR-Directorate of Rapeseed-Mustard Research, state universities and KVKs are key sources.

Sources: ICAR crop/state advisories; ICAR-DRMR; Government crop statistics; peer-reviewed UAV spray research.

Source: `09_Rapeseed-Mustard.docx` · Google Drive file id `1kABN8eidKAUofZcgQjDsk1z8euQWeGkt` · folder “4. Crop wise drone spraying information”

Sugarcane

- Sugarcane – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Uttar Pradesh, Maharashtra, Karnataka and Tamil Nadu are major states; Andhra Pradesh, Gujarat, Bihar, Haryana, Punjab and others also grow cane.

Major growing districts. Muzaffarnagar, Meerut, Baghpat, Shamli and Bijnor in UP; Kolhapur, Sangli, Pune and Solapur in Maharashtra; Belagavi and Bagalkot in Karnataka; major cane districts in Tamil Nadu and Andhra Pradesh.

Common pest and disease problems. Early shoot borer, top borer, internode borer, pyrilla, whitefly, scale insects and termites occur. Red rot, smut, wilt and grassy-shoot disease are important.

Common spraying requirements and products. IPM emphasizes healthy seed cane, resistant varieties, biological control, sanitation and targeted registered pesticides. ICAR publishes Sugarcane Crop Management Practices and maintains the Cane Adviser platform.

Suitable drone application information and spray volume. ICAR-NBAIR has demonstrated drone biopesticide application in sugarcane. Tall cane is suitable for aerial access, but mature canopy can shield lower leaves.

UAVs should be validated mainly for foliar targets; soil/root treatments require other methods. No reliable India-wide drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Borer and disease interventions are stage dependent. Biological control and sanitation can be more important than repeated foliar spraying. ICAR-Sugarcane Breeding Institute, state sugarcane research stations and KVKs are relevant.

Sources: ICAR Sugarcane Crop Management Practices; ICAR-NBAIR drone demonstrations; Government sugarcane statistics; state research institutes; peer-reviewed UAV literature.

Source: `10_Sugarcane.docx` · Google Drive file id `1gXtP7qsx2wnwKUBZuxxjdQD2AP28PsUO` · folder "4. Crop wise drone spraying information"

Potato

• Potato – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Uttar Pradesh, West Bengal, Bihar, Gujarat, Madhya Pradesh and Punjab are major potato regions.

Major growing districts. Agra, Farrukhabad, Kannauj and Aligarh in UP; Hooghly, Bardhaman and Nadia in West Bengal; potato belts of Bihar; Sabarkantha and Banaskantha in Gujarat; and major Punjab/MP production districts.

Common pest and disease problems. Late blight and early blight are major diseases. Aphids, potato tuber moth, cutworms and other insects also occur.

Common spraying requirements and products. Potato has frequent pesticide requirements because the crop is short-duration and susceptible to several pests and diseases. ICAR-Central Potato Research Institute has directly evaluated fungicides, insecticides and herbicides by drone, measuring coverage, penetration, drift and phytotoxicity.

Suitable drone application information and spray volume. ICAR-CPRI used a six-propeller UAV with a 20-L tank, four centrifugal atomizing nozzles, 4-m swath, 12.6 km/h speed, 2-m height and 60 L/h flow. It covered about 1.26 ha in 15 minutes. The trials reported good top/middle/bottom penetration and no observed phytotoxicity in tested products.

Number and timing of applications and relevant government/agricultural-university information. ICAR-CPRI reports approximately 20 L/ha was sufficient in its potato drone trials versus 500–750 L/ha conventional water use. This is crop- and system-specific and must not be transferred to other crops. Timing/number of sprays should follow disease forecasting, pest pressure and current labels.

Sources: ICAR-Central Potato Research Institute, Drone Based Potato Crop Management Technologies; Government agricultural-drone SOP framework; ICAR crop advisories; peer-reviewed potato UAV research.

Source: `11_Potato.docx` · Google Drive file id `1QvoqkqG4jm7oC2JrUoc1nLuh9KNEQRxC` · folder "4. Crop wise drone spraying information"

Tomato

• Tomato – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Andhra Pradesh, Madhya Pradesh, Karnataka, Gujarat, Odisha, West Bengal, Chhattisgarh, Bihar, Telangana, Maharashtra and Tamil Nadu.

Major growing districts. Kurnool, Anantapur/Sri Sathya Sai, Chittoor/Tirupati and Prakasam in Andhra Pradesh; Kolar and Chikkaballapur in Karnataka; major belts of MP, Telangana, Maharashtra and Odisha.

Common pest and disease problems. Fruit borer, whitefly, thrips, aphids, leaf miner and mites are common. Tomato leaf curl virus, early/late blight, bacterial wilt and damping-off are important diseases.

Common spraying requirements and products. ICAR-NRIPM includes tomato in its pesticide calculator. Management combines nursery sanitation, vector control, traps, biological methods and registered insecticide/fungicide use. Whitefly control is especially important for virus management.

Suitable drone application information and spray volume. Open-field tomato can receive UAV foliar applications, but complex canopy and leaf undersides require good deposition. Drones may reduce ground traffic damage. No authoritative India-wide drone volume was identified.

Number and timing of applications and relevant government/agricultural-university information. Whitefly/vector management begins in nursery and continues through crop establishment; fungicides are risk/symptom based; fruit-borer sprays are scouting and stage based. State horticulture departments, ICAR-NRIPM, IIHR and KVKs are relevant.

Sources: National Horticulture Board tomato statistics; ICAR-NRIPM; ICAR vegetable advisories; state agricultural universities; peer-reviewed UAV vegetable-spraying research.

Source: `12_Tomato.docx` · Google Drive file id `1QnCwq3P0CWNNwgkfol83-zoOr0qE00fF` · folder “4. Crop wise drone spraying information”

Chilli

- Chilli – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Andhra Pradesh, Telangana, Karnataka, Madhya Pradesh and Odisha are major regions; other states also cultivate chilli.

Major growing districts. Guntur, Bapatla, Palnadu, Prakasam and Krishna in Andhra Pradesh; Khammam, Warangal/Hanamkonda and Mahabubabad in Telangana; Byadgi/Haveri and Raichur in Karnataka.

Common pest and disease problems. Thrips, mites, aphids, whiteflies and fruit borers are common. Leaf-curl/viral complexes, anthracnose/fruit rot, powdery mildew and leaf spots are important.

Common spraying requirements and products. ICAR-NRIPM includes chilli in its pesticide calculator. Management commonly combines sticky traps, biological control, neem-based options where appropriate and registered insecticides/fungicides. Resistance management is important in repeated spraying.

Suitable drone application information and spray volume. Drone spraying is potentially useful in open-field chilli, but small leaves and dense foliage make coverage difficult. Thrips can occupy protected leaf/flower sites. No authoritative India-wide drone volume was found; a validated local SOP is needed.

Number and timing of applications and relevant government/agricultural-university information. Thrips and mite treatments should follow scouting; fungal disease applications are weather and symptom based; virus management is mainly preventive through vector control and sanitation. ICAR-IIHR, ICAR-NRIPM, state universities and KVKs are relevant.

Sources: NHB chilli statistics; ICAR-NRIPM; ICAR vegetable advisories; agricultural-university IPM recommendations; peer-reviewed UAV research.

Source: `13_Chilli.docx` · Google Drive file id `1UydvjByDJsonxNYShtBz-7Ex7MypIKnX` · folder “4. Crop wise drone spraying information”

Onion

• Onion – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra, Madhya Pradesh, Karnataka, Bihar, Rajasthan, Andhra Pradesh, Haryana, West Bengal, Gujarat and Uttar Pradesh.

Major growing districts. Nashik, Ahmednagar, Pune, Solapur and Dhule in Maharashtra; Indore, Ujjain and Mandsaur in MP; Gadag, Dharwad and Chitradurga in Karnataka; major onion districts of Bihar, Rajasthan, Gujarat and Andhra Pradesh.

Common pest and disease problems. Thrips are the principal insect pest. Purple blotch, Stemphylium blight, downy mildew and basal rot are important diseases.

Common spraying requirements and products. Management combines sanitation, irrigation management, scouting and targeted registered insecticide/fungicide use. Thrips control requires good coverage because insects shelter in leaf axils.

Suitable drone application information and spray volume. Onion leaves are narrow and upright, making interception by UAV droplets more difficult than in broad-leaf crops. Drones are potentially useful for timely foliar sprays, but efficacy must be validated. No reliable crop-specific Indian drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Thrips treatments should follow monitoring and local thresholds; disease sprays are weather/risk based. ICAR-Directorate of Onion and Garlic Research, NHB, state horticulture departments and agricultural universities are relevant.

Sources: NHB onion production report; ICAR-Directorate of Onion and Garlic Research; ICAR-NRIPM resources; state advisories; peer-reviewed UAV research.

Source: `14_Onion.docx` · Google Drive file id `1lSKieKtHN8nAJL2i3Vl6tut8TO0GHNlc` · folder “4. Crop wise drone spraying information”

Mango

• Mango – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade

brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Uttar Pradesh, Andhra Pradesh, Maharashtra, Karnataka, Bihar, Gujarat, Telangana, Tamil Nadu, West Bengal, Odisha and Madhya Pradesh are major mango regions.

Major growing districts. NHB identifies Krishna, East/West Godavari, Visakhapatnam, Srikakulam and Chittoor in AP; Ratnagiri, Sindhudurg and Raigad in Maharashtra; Kolar and Bengaluru/Tumakuru belts in Karnataka; Junagadh, Valsad and Surat in Gujarat; Saharanpur, Bulandshahr, Lucknow and Varanasi in UP; Malda and Murshidabad in West Bengal.

Common pest and disease problems. Mango hopper, mealybug, fruit fly, scales and shoot gall maker occur. Powdery mildew, anthracnose and dieback complexes are important.

Common spraying requirements and products. ICAR's 2025 advisory gives mango-hopper examples around flower-bud initiation/emergence of inflorescence, including imidacloprid or cytraniliprole where appropriate. Disease programs depend on flowering, fruit development and weather. Current label approval is mandatory.

Suitable drone application information and spray volume. Mango is a promising but technically difficult orchard-drone crop. Drones can reach orchard blocks without ground compaction, but outer-canopy coverage does not guarantee inner-canopy deposition. UAV trials should measure outer, middle and inner canopy deposition. ICAR-NBAIR has demonstrated drone biopesticide application in mango.

Number and timing of applications and relevant government/agricultural-university information. No authoritative India-wide mango drone volume was found. Orchard volume depends on tree size, canopy density and formulation and should be validated experimentally rather than copied from field crops.

Sources: NHB Mango crop database; ICAR Kharif Agro-Advisory 2025; ICAR-NBAIR drone demonstrations; ICAR 2026 spray-science workshop; peer-reviewed orchard-UAV research.

Source: `15_Mango.docx` · Google Drive file id `1Y7eeMM1KGbIGzduea5iz2rwBvd0v8lK7` · folder “4. Crop wise drone spraying information”

Banana

• Banana – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra, Tamil Nadu, Karnataka, Gujarat, Andhra Pradesh, Madhya Pradesh, Assam, Bihar and Kerala.

Major growing districts. Jalgaon and nearby Maharashtra belts; Theni, Tiruchirappalli, Erode and Coimbatore in Tamil Nadu; Anand, Bharuch, Surat and Narmada in Gujarat; East/West Godavari and other AP belts; important Karnataka and Kerala districts.

Common pest and disease problems. Pseudostem borer, rhizome/corm weevil, thrips, aphids and mites occur. Sigatoka/leaf-spot complexes, Fusarium wilt, bacterial wilt and bunch diseases are important.

Common spraying requirements and products. Management combines clean planting material, sanitation, removal of infected leaves, vector control and registered chemical applications where needed. Many disease problems require cultural and planting-material measures in addition to spraying.

Suitable drone application information and spray volume. Banana's tall broad leaves can be reached by drones, but canopy and wind interactions are substantial. UAVs may help with foliar applications where

ground access is difficult. No reliable India-wide drone volume was identified; plant height and canopy stage should be part of any validated SOP.

Number and timing of applications and relevant government/agricultural-university information. Leaf-spot management is weather/disease based; borer and weevil management often needs integrated non-foliar tactics. ICAR-National Research Centre for Banana, NHB, state horticulture departments and universities are key sources.

Sources: NHB Banana crop database; ICAR-NRCB and state advisories; ICAR-NBAIR demonstrations.

Source: `16_Banana.docx` · Google Drive file id `1OnveO5dNx4xobeZwRhZtul1wyVPu7J0d` · folder "4. Crop wise drone spraying information"

Grapes

• Grapes – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra is dominant, followed by Karnataka and important areas of Tamil Nadu and Andhra Pradesh/Telangana; northern production also occurs in Punjab, Haryana and UP.

Major growing districts. Nashik, Sangli, Ahmednagar, Pune, Satara, Solapur and Osmanabad/Dharashiv in Maharashtra; Vijayapura, Bagalkot and Bengaluru/Kolar belts in Karnataka; selected Tamil Nadu and AP/Telangana vineyards.

Common pest and disease problems. Thrips, mealybugs, mites and leafhoppers occur. Downy mildew, powdery mildew, anthracnose and bunch rots are major diseases.

Common spraying requirements and products. Grape disease programs are strongly phenology- and weather-dependent. Fungicide rotation is important because resistance risk is high. Export vineyards must also manage residue requirements. Product selection must follow current label and local NRCG recommendations.

Suitable drone application information and spray volume. Vineyards are technically suitable for UAVs only after careful row-following and canopy-deposition validation. Trellis geometry and dense foliage can cause uneven deposition. No universally validated Indian drone volume was found; canopy-volume and phenology should guide experimental protocols.

Number and timing of applications and relevant government/agricultural-university information. Applications vary by disease pressure, cultivar and season. ICAR-National Research Centre for Grapes is a key source. ICAR held a 2026 workshop on spray science and orchard spraying, emphasizing droplet impact, absorption and canopy problems.

Sources: NHB Grape crop database; ICAR-NRCG; ICAR 2026 spray-science workshop; state grape advisories; peer-reviewed UAV vineyard-spraying research.

Source: `17_Grapes.docx` · Google Drive file id `1nArJd15oez9ybPBGcjjnETW_uJyCz5ar` · folder "4. Crop wise drone spraying information"

Pomegranate

• Pomegranate – Crop-Wise Drone Spraying Information

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in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra is dominant, followed by Karnataka, Gujarat, Rajasthan, Tamil Nadu and Andhra Pradesh/Telangana.

Major growing districts. Solapur, Sangli, Nashik, Ahmednagar, Pune, Dhule, Chhatrapati Sambhajinagar, Satara, Dharashiv and Latur in Maharashtra; Vijayapura, Koppal, Dharwad, Tumakuru and Bagalkot in Karnataka; Anantapur and other southern belts.

Common pest and disease problems. Anar butterfly/fruit borer, thrips, aphids, mealybugs and mites occur. Bacterial blight, Alternaria fruit spot, anthracnose and wilt complexes are important.

Common spraying requirements and products. ICAR's 2025 advisory gives pomegranate-specific examples for anar butterfly control and wilt management and links applications to timing. Wilt requires integrated root-zone and sanitation measures, not simply foliar spraying.

Suitable drone application information and spray volume. Drone spraying is promising for orchard canopy applications, but dense foliage and fruit protection make deposition validation essential. No authoritative India-wide drone volume was found. Tree size and canopy density must determine experimental settings.

Number and timing of applications and relevant government/agricultural-university information. ICAR gives a timing example for anar butterfly: an initial spray in the first week of May followed by another after 15–20 days if required, but this is advisory-specific and should not be generalized. ICAR-NRC Pomegranate and NHB are key sources.

Sources: NHB Pomegranate database; ICAR Kharif Agro-Advisory 2025; ICAR horticulture institutes; state university recommendations; peer-reviewed UAV orchard research.

Source: `18_Pomegranate.docx` · Google Drive file id `1UpYpiSIp_CLFk9ZpubgMhy3Q2W1Z7jlS` · folder “4. Crop wise drone spraying information”

Citrus

• Citrus – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Maharashtra, Madhya Pradesh, Punjab, Rajasthan, Andhra Pradesh, Telangana, Karnataka, Assam and Bihar are important citrus regions.

Major growing districts. Nagpur and Wardha in Maharashtra; citrus belts of MP; Fazilka and Muktsar for kinnow in Punjab; northern Rajasthan; Nalgonda/Suryapet and other Telangana sweet-orange belts; Anantapur and Kurnool in AP.

Common pest and disease problems. Citrus psylla, leaf miner, aphids, scales, mites and fruit flies are common. Citrus canker, huanglongbing/greening, tristeza and Phytophthora/gummosis complexes are important.

Common spraying requirements and products. Vector management is central to citrus greening. Canker management combines sanitation and approved crop protection; Phytophthora requires drainage/root-zone management. Chemical choice must follow current state and label recommendations.

Suitable drone application information and spray volume. Citrus has a dense three-dimensional canopy, so UAV spraying is more difficult than open-field crops. Drones can be used for outer-canopy foliar treatments but inner-canopy deposition must be measured. No reliable India-wide drone volume was identified.

Number and timing of applications and relevant government/agricultural-university information. Psyllid management is tied to flush periods; disease protection is linked to new flush and rainfall risk. ICAR-Central Citrus Research Institute, NHB, state horticulture departments and universities are key sources.

Sources: NHB horticulture statistics; ICAR-Central Citrus Research Institute; state citrus advisories; ICAR spray-science material; peer-reviewed UAV orchard research.

Source: `19_Citrus.docx` · Google Drive file id `17e5TcZA3ldtyuCyi7giGuEjKIQnUTPLz` · folder "4. Crop wise drone spraying information"

Coconut

• Coconut – Crop-Wise Drone Spraying Information

State and district information is presented as major or representative production belts identified from Government of India, National Horticulture Board, ICAR and agricultural-university material; it is not an exhaustive district census. Pest and disease information is drawn from official crop advisories and plant-protection literature. Products are identified mainly by active ingredient or formulation rather than trade brand. Any pesticide used in practice must be currently registered and label-approved for the crop and target in India and must follow the current label, state advisory and applicable agricultural-drone SOP. Drone water volume is stated only where a crop-specific authoritative UAV trial was identified. Conventional ground-sprayer water volumes must not automatically be transferred to drones.

Major growing states. Tamil Nadu, Karnataka, Kerala and Andhra Pradesh are major producers; Maharashtra, Odisha and other tropical/coastal regions also contribute.

Major growing districts. Coimbatore, Tiruppur and Thanjavur belts in Tamil Nadu; Tumakuru, Hassan and coastal Karnataka; Alappuzha, Thrissur, Kozhikode and Kannur in Kerala; East/West Godavari and Krishna belts in Andhra Pradesh.

Common pest and disease problems. Rhinoceros beetle, red palm weevil, eriophyid mite, black-headed caterpillar and scales are important. Basal stem rot, bud rot and other foliar/inflorescence diseases occur.

Common spraying requirements and products. Management commonly combines sanitation, crown management, pheromone traps, biological control and targeted chemical measures. Many coconut pests cannot be solved by foliar spraying alone because they occupy the crown, trunk or soil/root zone.

Suitable drone application information and spray volume. Drone use is attractive for tall palms because it can reach the crown without climbing. However, wind and tree height make deposition difficult. UAV treatment should be restricted to targets and formulations validated for aerial delivery. No reliable India-wide drone volume was found.

Number and timing of applications and relevant government/agricultural-university information. Rhinoceros beetle and red palm weevil management relies heavily on integrated methods and traps. ICAR-CPCRI, Coconut Development Board and ICAR-NBAIR are relevant; ICAR-NBAIR has demonstrated drone biopesticide application in coconut.

Sources: NHB Coconut database; ICAR-CPCRI; Coconut Development Board; ICAR-NBAIR drone demonstrations; peer-reviewed UAV plantation-spraying research.

Source: `20_Coconut.docx` · Google Drive file id `13IbcBpoKpRCWQdQwBCBkEyenjxG3Bli1` · folder "4. Crop wise drone spraying information"

5. State-Wise Agricultural Information

state-wise Indian agricultural information — major crops, districts, seasons, crop-protection challenges, drone adoption, government schemes, agricultural universities and FPOs

In this section: State_Wise_Agricultural_Information_28_States, State_Wise_Agricultural_Information_Database

State Wise Agricultural Information 28 States

State-Wise Agricultural Information – India

Database covering all 28 Indian states for agricultural-drone deployment planning. Each state profile includes crops, districts, seasons, crop-protection challenges, drone adoption, government schemes, agricultural universities, departments, market hubs and FPO/cooperative opportunities.

Andhra Pradesh

Major crops: Rice, groundnut, cotton, maize, chilli, tobacco, sugarcane, pulses, mango, banana

Major agricultural districts: East/West Godavari, Krishna, Guntur/Palnadu, Bapatla, Nellore, Kurnool, Anantapur/Sri Sathya Sai, Prakasam, Chittoor/Tirupati

Major farming seasons: Kharif, Rabi, summer irrigated crops

Major crop-protection challenges: Cyclones/floods; Rayalaseema drought; cotton/chilli pests; salinity

Drone adoption information: 96 Namo Drone Didi SHGs in Mar-2026; 108 LFC-distributed SHG drones reported Jan-2026

Agricultural universities: ANGRAU; Dr YSR Horticultural University; SVVU; AP Fisheries University

Important agriculture departments: Department of Agriculture; Horticulture Department; AP State Agricultural Marketing Board; SERP/SRLM

Major agri-input/wholesale market hubs: Guntur/Bapatla, Vijayawada/Krishna, Kurnool, Anantapur, Duggirala, Eluru, Rajahmundry/Kakinada

FPOs/cooperatives: Chilli, rice, cotton, groundnut and horticulture FPOs/PACS; verify current SFAC/NABARD/ state registry

Arunachal Pradesh

Major crops: Rice, maize, millets, pulses, oilseeds, large cardamom, ginger, turmeric, kiwi, orange

Major agricultural districts: Papum Pare, Namsai, East Siang, West Siang, Lower/Upper Subansiri, Lohit, West Kameng

Major farming seasons: Kharif dominant; limited rabi; elevation-specific horticulture

Major crop-protection challenges: Steep terrain, landslides, excess rain, fragmented farms, logistics

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release; treat as emerging and verify state inventory

Agricultural universities: No state agricultural university listed in current ICAR SAU list; use NE/ICAR institutions and KVKs

Important agriculture departments: Department of Agriculture; Horticulture; SRLM; district KVK network

Major agri-input/wholesale market hubs: Itanagar/Naharlagun, Namsai, Pasighat; Assam gateways for inputs

FPOs/cooperatives: FPO/PACS mapping should use SFAC/NABARD/state registry; prioritize clustered horticulture groups

Assam

Major crops: Rice, tea, jute, mustard, pulses, sugarcane, potato, vegetables, banana, pineapple, citrus

Major agricultural districts: Nagaon, Barpeta, Kamrup, Darrang, Sonitpur, Lakhimpur, Cachar, Jorhat, Golaghat

Major farming seasons: Ahu/Sali/Boro rice; kharif and rabi crops

Major crop-protection challenges: Flood/erosion, waterlogging, humidity diseases, fragmented farms

Drone adoption information: 9 Namo Drone Didi SHGs in Mar-2026; 28 LFC-distributed SHG drones Jan-2026

Agricultural universities: Assam Agricultural University; Assam Veterinary & Fishery University

Important agriculture departments: Agriculture Department; Horticulture; Assam State Agricultural Marketing Board; ASRLM

Major agri-input/wholesale market hubs: Guwahati, Nagaon, Jorhat, Dibrugarh, Silchar, Barpeta

FPOs/cooperatives: Tea, rice, horticulture FPOs/cooperatives; verify current registry

Bihar

Major crops: Rice, wheat, maize, pulses, oilseeds, sugarcane, potato, vegetables, litchi, banana, mango

Major agricultural districts: Muzaffarpur, Vaishali, Samastipur, Darbhanga, East/West Champaran, Purnia, Katihar, Rohtas, Nalanda, Begusarai

Major farming seasons: Kharif, Rabi, Zaid

Major crop-protection challenges: Flood/drought variability, small holdings, storage/marketing, pests

Drone adoption information: 5 Namo Drone Didi SHGs in Mar-2026; 32 LFC-distributed SHG drones Jan-2026

Agricultural universities: Bihar Agricultural University; Dr RP Central Agricultural University; Bihar Animal Sciences University

Important agriculture departments: Agriculture; Horticulture; Bihar Agricultural Marketing Board; JEEViKA

Major agri-input/wholesale market hubs: Patna, Purnia/Gulabbagh, Muzaffarpur, Darbhanga, Samastipur, Hajipur

FPOs/cooperatives: Maize, litchi, rice and vegetable FPOs/PACS; verify SFAC/NABARD

Chhattisgarh

Major crops: Rice, maize, pulses, oilseeds, wheat, sugarcane, vegetables, horticulture

Major agricultural districts: Raipur, Durg, Rajnandgaon, Balod, Bemetara, Dhamtari, Mahasamund, Bilaspur, Janjgir-Champa, Surguja, Bastar

Major farming seasons: Kharif rice; rabi pulses/oilseeds/wheat

Major crop-protection challenges: Rice pests/diseases, drought pockets, soil fertility, remote logistics

Drone adoption information: 12 Namo Drone Didi SHGs Mar-2026; 15 LFC-distributed Jan-2026

Agricultural universities: Indira Gandhi Krishi Vishwavidyalaya; Chhattisgarh Kamdhenu University; MG University of Horticulture & Forestry

Important agriculture departments: Agriculture; Horticulture; State Agricultural Marketing Board; Bihan/SRLM

Major agri-input/wholesale market hubs: Raipur, Durg, Rajnandgaon, Dhamtari, Bilaspur, Jagdalpur

FPOs/cooperatives: Rice/pulse FPOs and tribal producer groups; verify registry

Goa

Major crops: Rice, coconut, cashew, arecanut, mango, banana, vegetables, spices

Major agricultural districts: North Goa and South Goa; Pernem, Bicholim, Bardez, Tiswadi, Salcete, Canacona

Major farming seasons: Kharif rice; perennial horticulture; rabi/summer vegetables

Major crop-protection challenges: Small holdings, monsoon, plantation pests, limited large-field mechanization

Drone adoption information: 1 LFC-distributed SHG drone reported Jan-2026

Agricultural universities: No state agricultural university in current ICAR SAU list; Goa University and ICAR-CCARI Goa are relevant

Important agriculture departments: Agriculture; Horticulture; Goa State Agricultural Marketing Board; Goa SRLM

Major agri-input/wholesale market hubs: Mapusa, Ponda, Margao and Panaji-area trade hubs

FPOs/cooperatives: Cashew/coconut/vegetable cooperatives and FPOs; verify state registry

Gujarat

Major crops: Cotton, groundnut, wheat, bajra, castor, cumin, sesame, pulses, sugarcane, banana, mango, potato

Major agricultural districts: Rajkot, Junagadh, Amreli, Bhavnagar, Jamnagar, Surendranagar, Banaskantha, Sabarkantha, Anand, Kheda, Bharuch, Surat, Kutch

Major farming seasons: Kharif, Rabi, summer/irrigated

Major crop-protection challenges: Drought/water stress, salinity, cotton pests, groundnut disease, heat

Drone adoption information: 18 Namo Drone Didi SHGs Mar-2026; 58 LFC-distributed Jan-2026

Agricultural universities: Anand Agricultural University; Junagadh Agricultural University; Navsari AU; SDAU; Kamdhenu University

Important agriculture departments: Agriculture; Horticulture; Gujarat State Agricultural Marketing Board; GULM

Major agri-input/wholesale market hubs: Unjha, Rajkot, Gondal, Junagadh, Deesa, Anand, Ahmedabad

FPOs/cooperatives: Cotton/groundnut/spice/dairy-linked FPOs and cooperatives

Haryana

Major crops: Wheat, rice, cotton, mustard, bajra, sugarcane, fodder, vegetables

Major agricultural districts: Karnal, Kurukshetra, Ambala, Yamunanagar, Hisar, Sirsa, Fatehabad, Bhiwani, Jind, Kaithal, Rohtak, Rewari

Major farming seasons: Kharif, Rabi, summer fodder/vegetables

Major crop-protection challenges: Groundwater depletion, rice-wheat monocropping, residue, heat, resistance

Drone adoption information: 22 Namo Drone Didi SHGs Mar-2026; 102 LFC-distributed Jan-2026

Agricultural universities: CCS Haryana Agricultural University; Maharana Pratap Horticultural University; LUVAS

Important agriculture departments: Agriculture; Horticulture; Haryana State Agricultural Marketing Board; HSRLM

Major agri-input/wholesale market hubs: Karnal, Hisar, Sirsa, Fatehabad, Kaithal, Kurukshetra, Ambala

FPOs/cooperatives: Rice/wheat/cotton FPOs and cooperatives; strong CHC potential

Himachal Pradesh

Major crops: Apple, maize, wheat, barley, rice, vegetables, stone fruits, seed potato

Major agricultural districts: Shimla, Kullu, Kinnaur, Solan, Mandi, Sirmaur, Chamba, Kangra

Major farming seasons: Kharif/Rabi; temperate horticulture by elevation

Major crop-protection challenges: Hail/frost, landslides, orchard pests/disease, fragmented holdings

Drone adoption information: 4 Namo Drone Didi SHGs Mar-2026; 4 LFC-distributed Jan-2026

Agricultural universities: CSK HP Krishi Vishvavidyalaya; Dr YS Parmar University of Horticulture & Forestry

Important agriculture departments: Agriculture; Horticulture; HPMC/marketing; HP SRLM

Major agri-input/wholesale market hubs: Shimla, Solan, Parwanoo, Mandi, Kullu, Bhattakufar

FPOs/cooperatives: Apple/vegetable FPOs and orchard cooperatives

Jharkhand

Major crops: Rice, maize, pulses, oilseeds, wheat, vegetables, lac, horticulture

Major agricultural districts: Ranchi, East/West Singhbhum, Hazaribagh, Ramgarh, Dumka, Deoghar, Gumla, Lohardaga, Palamu, Latehar

Major farming seasons: Kharif dominant; rabi moisture/irrigation dependent

Major crop-protection challenges: Rainfed farming, drought, soil acidity, low irrigation, market access

Drone adoption information: 1 Namo Drone Didi SHG Mar-2026; 15 LFC-distributed Jan-2026

Agricultural universities: Birsa Agricultural University

Important agriculture departments: Agriculture; Horticulture; Jharkhand State Agricultural Marketing Board; JSLPS

Major agri-input/wholesale market hubs: Ranchi, Hazaribagh, Jamshedpur, Deoghar, Dumka

FPOs/cooperatives: Rice/pulse/vegetable FPOs and tribal producer groups

Karnataka

Major crops: Rice, maize, ragi, pulses, cotton, sugarcane, groundnut, coffee, arecanut, coconut, grapes, banana, chilli

Major agricultural districts: Belagavi, Dharwad, Haveri, Davanagere, Shivamogga, Tumakuru, Mandya, Mysuru, Raichur, Kalaburagi, Vijayapura, Kolar, Chikkaballapur, Kodagu

Major farming seasons: Kharif, Rabi, summer irrigated; plantation cycles

Major crop-protection challenges: Drought, water stress, cotton/chilli pests, coffee/plantation diseases

Drone adoption information: 82 Namo Drone Didi SHGs Mar-2026; 145 LFC-distributed Jan-2026

Agricultural universities: UAS Bengaluru, UAS Dharwad, UAS Raichur, UHS Bagalkot, KSNUAHS Shivamogga, KVAFSU

Important agriculture departments: Agriculture; Horticulture; Karnataka Agricultural Marketing Board; KSRLM

Major agri-input/wholesale market hubs: Hubballi, Belagavi, Davanagere, Raichur, Kalaburagi, Vijayapura, Bengaluru, Kolar

FPOs/cooperatives: Large FPO/CHC ecosystem; strong drone-service opportunity

Kerala

Major crops: Rice, coconut, rubber, pepper, cardamom, coffee, banana, vegetables, cashew

Major agricultural districts: Palakkad, Thrissur, Alappuzha, Kottayam, Idukki, Wayanad, Kozhikode, Kannur, Kasaragod

Major farming seasons: Monsoon crops; rabi/summer vegetables; perennial plantations

Major crop-protection challenges: High rainfall/floods/landslides, fungal diseases, plantation pests, fragmented farms

Drone adoption information: 2 Namo Drone Didi SHGs Mar-2026; 51 LFC-distributed Jan-2026

Agricultural universities: Kerala Agricultural University; KVASU; KUFOS

Important agriculture departments: Agriculture; Horticulture; Kerala State Agricultural Marketing Board; Kudumbashree/SRLM

Major agri-input/wholesale market hubs: Palakkad, Thrissur, Kottayam, Kochi/Aluva, Kozhikode, Kannur, Kalpetta

FPOs/cooperatives: Coconut/plantation/vegetable cooperatives and FPOs

Madhya Pradesh

Major crops: Soybean, wheat, gram, maize, pulses, oilseeds, cotton, mustard, garlic, onion

Major agricultural districts: Indore, Ujjain, Dewas, Sehore, Bhopal, Vidisha, Sagar, Raisen, Chhindwara, Jabalpur, Mandsaur, Neemuch, Ratlam, Khandwa, Khargone

Major farming seasons: Kharif soybean/maize/cotton; Rabi wheat/gram/mustard

Major crop-protection challenges: Soybean pests/diseases, drought, weeds, storage and price volatility

Drone adoption information: 34 Namo Drone Didi SHGs Mar-2026; 89 LFC-distributed Jan-2026

Agricultural universities: JNKVV Jabalpur; RVSKVV Gwalior; NDVSU

Important agriculture departments: Agriculture; Horticulture; MP Mandi Board; SRLM

Major agri-input/wholesale market hubs: Indore, Ujjain, Dewas, Mandsaur, Neemuch, Ratlam, Sehore, Bhopal

FPOs/cooperatives: Soybean/wheat/pulse FPOs and CHCs

Maharashtra

Major crops: Cotton, soybean, sugarcane, tur, chickpea, wheat, onion, grapes, pomegranate, banana, citrus

Major agricultural districts: Nashik, Ahmednagar, Pune, Solapur, Sangli, Kolhapur, Satara, Jalgaon, Dhule, Akola, Amravati, Yavatmal, Latur, Nanded, Nagpur, Wardha

Major farming seasons: Kharif, Rabi, summer irrigated; horticulture phenological cycles

Major crop-protection challenges: Drought/water scarcity, cotton/pulse pests, grape/pomegranate diseases, onion price volatility

Drone adoption information: 30 Namo Drone Didi SHGs Mar-2026; 60 LFC-distributed Jan-2026

Agricultural universities: MPKV Rahuri; PDKV Akola; VNMKV Parbhani; DBSKKV Dapoli; MAFSU

Important agriculture departments: Agriculture; Horticulture; Maharashtra State Agricultural Marketing Board; MAVIM/SRLM

Major agri-input/wholesale market hubs: Nashik/Lasalgaon, Pune, Ahmednagar, Solapur, Sangli, Jalgaon, Akola, Latur

FPOs/cooperatives: Onion/grape/pomegranate/cotton/soybean FPOs; high commercial potential

Manipur

Major crops: Rice, maize, pulses, oilseeds, vegetables, pineapple, orange, ginger, turmeric

Major agricultural districts: Imphal East/West, Bishnupur, Thoubal, Kakching, Churachandpur, Ukhrul, Senapati

Major farming seasons: Kharif rice/maize; rabi vegetables/pulses

Major crop-protection challenges: Hilly terrain, valley flooding, erosion, market access, fragmented farms

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release

Agricultural universities: Central Agricultural University, Imphal

Important agriculture departments: Agriculture; Horticulture; Manipur State Agricultural Marketing; SRLM

Major agri-input/wholesale market hubs: Imphal, Thoubal, Kakching; Assam gateways

FPOs/cooperatives: Rice/horticulture FPOs and cooperatives

Meghalaya

Major crops: Rice, maize, potato, ginger, turmeric, pineapple, banana, citrus, vegetables

Major agricultural districts: East/West Khasi Hills, Ri-Bhoi, East/West Garo Hills, West Jaintia Hills

Major farming seasons: Kharif and rabi vegetables/potato; horticulture by elevation

Major crop-protection challenges: Heavy rain, erosion, acidic soils, steep terrain, logistics

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release

Agricultural universities: No state agricultural university in current ICAR SAU list; ICAR/NEH and KVK network

Important agriculture departments: Agriculture; Horticulture; Meghalaya State Agricultural Marketing Board; MSRLS

Major agri-input/wholesale market hubs: Shillong, Byrnihat, Nongpoh, Tura, Jowai

FPOs/cooperatives: Horticulture FPOs/cooperatives; verify current registry

Mizoram

Major crops: Rice, maize, pulses, oilseeds, ginger, turmeric, chilli, vegetables, banana, orange, pineapple

Major agricultural districts: Aizawl, Lunglei, Champhai, Kolasib, Serchhip, Mamit, Lawngtlai, Saitual

Major farming seasons: Kharif dominant; horticulture by elevation

Major crop-protection challenges: Steep terrain, erosion, fragmented/shifting cultivation, logistics

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release

Agricultural universities: No state agricultural university in current ICAR SAU list; ICAR/NEH and KVK network

Important agriculture departments: Agriculture; Horticulture; Mizoram State Agricultural Marketing; SRLM

Major agri-input/wholesale market hubs: Aizawl, Lunglei, Kolasib, Champhai

FPOs/cooperatives: Horticulture/ginger/turmeric FPOs; verify registry

Nagaland

Major crops: Rice, maize, pulses, oilseeds, vegetables, pineapple, orange, ginger, turmeric, Naga chilli

Major agricultural districts: Dimapur, Kohima, Mokokchung, Wokha, Mon, Tuensang, Zunheboto, Phek

Major farming seasons: Kharif dominant; rabi vegetables/oilseeds

Major crop-protection challenges: Hilly terrain, erosion, access, fragmented farms, post-harvest gaps

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release

Agricultural universities: Nagaland University; NE/ICAR/KVK network

Important agriculture departments: Agriculture; Horticulture; Nagaland State Agricultural Marketing; SRLM

Major agri-input/wholesale market hubs: Dimapur, Kohima, Mokokchung

FPOs/cooperatives: Horticulture/spice FPOs and cooperatives

Odisha

Major crops: Rice, pulses, groundnut, maize, cotton, sugarcane, vegetables, coconut, cashew, turmeric

Major agricultural districts: Cuttack, Puri, Balasore, Mayurbhanj, Bargarh, Sambalpur, Kalahandi, Koraput, Ganjam, Dhenkanal, Angul

Major farming seasons: Kharif rice; rabi pulses/oilseeds/vegetables

Major crop-protection challenges: Cyclones, floods/drought, rice pests, waterlogging, soil fertility

Drone adoption information: 12 Namo Drone Didi SHGs Mar-2026; 16 LFC-distributed Jan-2026

Agricultural universities: OUAT Bhubaneswar

Important agriculture departments: Agriculture; Horticulture; Odisha State Agricultural Marketing Board; Odisha Livelihoods Mission

Major agri-input/wholesale market hubs: Bhubaneswar, Cuttack, Balasore, Bargarh, Sambalpur, Berhampur, Jeypore

FPOs/cooperatives: Rice/cotton/cashew FPOs and PACS

Punjab

Major crops: Rice, wheat, cotton, maize, mustard, sugarcane, vegetables, fodder

Major agricultural districts: Ludhiana, Patiala, Sangrur, Moga, Bathinda, Mansa, Muktsar, Firozpur, Fazilka, Amritsar, Tarn Taran, Gurdaspur

Major farming seasons: Kharif rice/cotton; Rabi wheat; summer maize/vegetables

Major crop-protection challenges: Groundwater depletion, monocropping, residue management, resistance, heat

Drone adoption information: 23 Namo Drone Didi SHGs Mar-2026; 57 LFC-distributed Jan-2026

Agricultural universities: Punjab Agricultural University; GADVASU

Important agriculture departments: Agriculture; Horticulture; Punjab Mandi Board; Punjab State Rural Livelihood Mission

Major agri-input/wholesale market hubs: Khanna, Ludhiana, Moga, Sangrur, Patiala, Bathinda, Mansa, Muktsar, Fazilka

FPOs/cooperatives: Large rice/wheat FPOs and CHCs; strong service economics

Rajasthan

Major crops: Wheat, mustard, gram, bajra, barley, guar, cotton, cumin, coriander, isabgol

Major agricultural districts: Sri Ganganagar, Hanumangarh, Alwar, Bharatpur, Kota, Baran, Bundi, Jhalawar, Nagaur, Bikaner, Jodhpur, Jaipur, Sikar

Major farming seasons: Kharif and Rabi; irrigated summer in command areas

Major crop-protection challenges: Aridity, drought, salinity, heat, wind erosion, irrigation scarcity

Drone adoption information: 19 Namo Drone Didi SHGs Mar-2026; 40 LFC-distributed Jan-2026

Agricultural universities: MPUAT Udaipur; SKRAU Bikaner; SKNAU Jobner; Agriculture Universities Kota/ Jodhpur; RAUVS

Important agriculture departments: Agriculture; Horticulture; Rajasthan State Agricultural Marketing Board; Rajeevika

Major agri-input/wholesale market hubs: Sri Ganganagar, Hanumangarh, Kota/Ramganj Mandi, Alwar, Jaipur, Nagaur, Jodhpur, Bikaner

FPOs/cooperatives: Mustard/cumin/coriander/wheat FPOs and CHCs

Sikkim

Major crops: Large cardamom, ginger, turmeric, maize, rice, buckwheat, vegetables, orange

Major agricultural districts: East, West, North, South and Pakyong districts

Major farming seasons: Kharif rainfed; rabi vegetables; perennial horticulture

Major crop-protection challenges: Steep slopes, landslides, erosion, small farms, access

Drone adoption information: No state-specific Namo Drone Didi count in cited Mar-2026 release

Agricultural universities: No state agricultural university in current ICAR SAU list; ICAR/NEH network

Important agriculture departments: Agriculture; Horticulture; Sikkim State Agricultural Marketing; SRLM

Major agri-input/wholesale market hubs: Gangtok, Singtam, Rangpo, Namchi; Siliguri supply chain

FPOs/cooperatives: Large-cardamom/ginger/orange FPOs; verify registry

Tamil Nadu

Major crops: Rice, sugarcane, cotton, groundnut, maize, millets, pulses, banana, coconut, turmeric, vegetables, mango

Major agricultural districts: Thanjavur, Tiruvarur, Nagapattinam/Mayiladuthurai, Tiruchirappalli, Erode, Coimbatore, Salem, Namakkal, Dindigul, Theni, Tiruppur, Villupuram, Krishnagiri

Major farming seasons: Kuruvai/Samba/Thaladi rice; Rabi and summer crops

Major crop-protection challenges: Water scarcity, cyclone/flood, rice/cotton pests, sugarcane disease, heat

Drone adoption information: 17 Namo Drone Didi SHGs Mar-2026; 44 LFC-distributed Jan-2026

Agricultural universities: TNAU Coimbatore; TANUVAS; TN Fisheries University

Important agriculture departments: Agriculture; Horticulture; Tamil Nadu Agricultural Marketing; TNSRLM

Major agri-input/wholesale market hubs: Coimbatore, Erode, Salem, Namakkal, Dindigul, Madurai, Thanjavur, Villupuram, Chennai/Koyambedu

FPOs/cooperatives: Rice/sugarcane/coconut/banana/vegetable FPOs and cooperatives

Telangana

Major crops: Rice, cotton, maize, soybean, red gram, green gram, chilli, turmeric, horticulture

Major agricultural districts: Nizamabad, Kamareddy, Karimnagar, Jagtial, Peddapalli, Warangal/Hanamkonda, Khammam, Suryapet, Nalgonda, Adilabad/Nirmal, Sangareddy

Major farming seasons: Kharif and Rabi; irrigated summer paddy in command areas

Major crop-protection challenges: Cotton pests, paddy pests/diseases, drought/heat, chilli pests, water/price volatility

Drone adoption information: 72 Namo Drone Didi SHGs Mar-2026; 81 LFC-distributed Jan-2026

Agricultural universities: PJTSAU; Sri Konda Laxman Telangana State Horticultural University; PVNRTVU

Important agriculture departments: Agriculture; Horticulture; Telangana State Agricultural Marketing; SERP

Major agri-input/wholesale market hubs: Hyderabad, Warangal, Nizamabad, Karimnagar, Khammam, Suryapet, Nalgonda, Adilabad

FPOs/cooperatives: Cotton/paddy/chilli FPOs; strong drone-service potential

Uttar Pradesh

Major crops: Rice, wheat, sugarcane, potato, maize, pulses, mustard, vegetables, mango

Major agricultural districts: Lakhimpur Kheri, Sitapur, Hardoi, Shahjahanpur, Bareilly, Meerut, Muzaffarnagar, Bijnor, Agra, Farrukhabad, Kannauj, Aligarh, Prayagraj, Varanasi, Gorakhpur

Major farming seasons: Kharif, Rabi, Zaid; sugarcane/horticulture longer cycles

Major crop-protection challenges: Flood/drought, sugarcane pests, rice-wheat pressure, potato blight, groundwater

Drone adoption information: 32 Namo Drone Didi SHGs Mar-2026; 128 LFC-distributed Jan-2026

Agricultural universities: CSAUA&T Kanpur; SVPUAT Meerut; NDUAT Ayodhya; BUAT Banda

Important agriculture departments: Agriculture; Horticulture; UP Mandi Parishad; UP State Rural Livelihood Mission

Major agri-input/wholesale market hubs: Kanpur, Agra, Lucknow, Meerut, Muzaffarnagar, Bareilly, Varanasi, Farrukhabad

FPOs/cooperatives: Wheat/rice/sugarcane/potato FPOs and CHCs; very large service market

Uttarakhand

Major crops: Rice, wheat, maize, millets, sugarcane, vegetables, apple, pear, citrus, spices

Major agricultural districts: Udham Singh Nagar, Nainital, Haridwar, Dehradun, Pauri, Almora, Tehri, Uttarkashi, Chamoli

Major farming seasons: Kharif/Rabi; hill horticulture by elevation

Major crop-protection challenges: Hills, landslides, rain variability, fragmented farms, wildlife damage

Drone adoption information: 3 Namo Drone Didi SHGs Mar-2026; 3 LFC-distributed Jan-2026

Agricultural universities: GBPUAT Pantnagar; VCSG Uttarakhand University of Horticulture & Forestry

Important agriculture departments: Agriculture; Horticulture; Uttarakhand Agricultural Produce Marketing Board; SRLM

Major agri-input/wholesale market hubs: Rudrapur, Kashipur, Haldwani, Haridwar, Dehradun, Pantnagar

FPOs/cooperatives: Apple/vegetable/FPO and cooperative clusters

West Bengal

Major crops: Rice, potato, jute, wheat, maize, mustard, vegetables, tea, mango, litchi, banana, pineapple

Major agricultural districts: Bardhaman, Nadia, Murshidabad, Hooghly, North/South 24 Parganas, Malda, Jalpaiguri, Uttar Dinajpur, Cooch Behar, Bankura

Major farming seasons: Aman/Aus/Boro rice; rabi/summer crops; tea/horticulture

Major crop-protection challenges: Flood/cyclone/coastal salinity, humidity diseases, rice/potato pests, fragmented farms

Drone adoption information: 7 Namo Drone Didi SHGs Mar-2026; 15 LFC-distributed Jan-2026

Agricultural universities: BCKV Mohanpur; Uttar Banga Krishi Viswavidyalaya; WBUAFS

Important agriculture departments: Agriculture; Horticulture; West Bengal State Agricultural Marketing Board; Anandadhara/SRLM

Major agri-input/wholesale market hubs: Bardhaman, Kalyani/Nadia, Siliguri, Malda, Hooghly, Kolkata/ Howrah, Cooch Behar

FPOs/cooperatives: Rice/potato/jute/horticulture FPOs and cooperatives

National drone-scheme reference: SMAM supports eligible institutional/FPO/CHC/individual drone acquisition or demonstration under the cited central provisions; Namo Drone Didi provides selected women SHGs 80% assistance up to ₹8 lakh for the drone package. State-level implementation, targets and eligibility should be checked with the current State Agriculture Department before procurement.

Primary source framework: ICAR State Agricultural Universities list; ICAR institutional directory; PIB/Ministry of Agriculture releases on SMAM and Namo Drone Didi; State Agriculture/Horticulture Departments; State Agricultural Marketing Boards/e-NAM; SFAC 10,000-FPO records; NABARD; KVKs and state agricultural universities.

Source: `State_Wise_Agricultural_Information_28_States.docx` · Google Drive file id `1yIezk62WMajyjuTmqqFeYOqIQRmOGEfu` · folder “5. State wise Agricultural Information”

State Wise Agricultural Information Database

Sheet: Sheet1

State	Major crops	Major agricultural districts	Major farming seasons	Major crop-protection challenges	Drone adoption information	Agricultural universities	Important agriculture departments	Major ag input/ wholesa market l
Andhra Pradesh	Rice, groundnut, cotton, maize, chilli, tobacco, sugarcane, pulses, mango, banana	East/West Godavari, Krishna, Guntur/ Palnadu, Bapatla, Nellore, Kurnool, Anantapur/Sri Sathya Sai, Prakasam, Chittoor/ Tirupati	Kharif, Rabi, summer irrigated crops	Cyclones/ floods; Rayalaseema drought; cotton/chilli pests; salinity	96 Namo Drone Didi SHGs in Mar-2026; 108 LFC-distributed SHG drones reported Jan-2026	ANGRAU; Dr YSR Horticultural University; SVVU; AP Fisheries University	Department of Agriculture; Horticulture Department; AP State Agricultural Marketing Board; SERP/ SRLM	Guntur/ Bapatla, Vijayawa Krishna, Kurnool, Anantap Duggiral Eluru, Rajahmu Kakinada
Arunachal Pradesh	Rice, maize, millets, pulses, oilseeds, large cardamom, ginger, turmeric, kiwi, orange	Papum Pare, Namsai, East Siang, West Siang, Lower/ Upper Subansiri, Lohit, West Kameng	Kharif dominant; limited rabi; elevation-specific horticulture	Steep terrain, landslides, excess rain, fragmented farms, logistics	No state-specific Namo Drone Didi count in cited Mar-2026 release; treat as emerging and verify state inventory	No state agricultural university listed in current ICAR SAU list; use NE/ ICAR institutions and KVKs	Department of Agriculture; Horticulture; SRLM; district KVK network	Itanagar/ Naharlag Namsai, Pasighat; Assam gateways inputs
Assam	Rice, tea, jute, mustard, pulses, sugarcane, potato, vegetables, banana, pineapple, citrus	Nagaon, Barpeta, Kamrup, Darrang, Sonitpur, Lakhimpur, Cachar, Jorhat, Golaghat	Ahu/Sali/ Boro rice; kharif and rabi crops	Flood/erosion, waterlogging, humidity diseases, fragmented farms	9 Namo Drone Didi SHGs in Mar-2026; 28 LFC-distributed SHG drones Jan-2026	Assam Agricultural University; Assam Veterinary & Fishery University	Agriculture Department; Horticulture; Assam State Agricultural Marketing Board; ASRLM	Guwahat Nagaon, Jorhat, Dibrugar Silchar, Barpeta
Bihar	Rice, wheat, maize, pulses, oilseeds, sugarcane, potato, vegetables, litchi, banana, mango	Muzaffarpur, Vaishali, Samastipur, Darbhanga, East/West Champaran, Purnia, Katihar, Rohtas, Nalanda, Begusarai	Kharif, Rabi, Zaid	Flood/drought variability, small holdings, storage/ marketing, pests	5 Namo Drone Didi SHGs in Mar-2026; 32 LFC-distributed SHG drones Jan-2026	Bihar Agricultural University; Dr RP Central Agricultural University; Bihar Animal Sciences University	Agriculture; Horticulture; Bihar Agricultural Marketing Board; JEEViKA	Patna, Pu Gulabbag Muzaffar Darbhan Samastip Hajipur
Chhattisgarh	Rice, maize, pulses, oilseeds, wheat, sugarcane, vegetables, horticulture	Raipur, Durg, Rajnandgaon, Balod, Bemetara, Dhamtari, Mahasamund, Bilaspur, Janjgir-Champa, Surguja, Bastar	Kharif rice; rabi pulses/ oilseeds/ wheat	Rice pests/ diseases, drought pockets, soil fertility, remote logistics	12 Namo Drone Didi SHGs Mar-2026; 15 LFC-distributed Jan-2026	Indira Gandhi Krishi Vishwavidyalaya; Chhattisgarh Kamdhenu University; MG University of Horticulture & Forestry	Agriculture; Horticulture; State Agricultural Marketing Board; Bihan/ SRLM	Raipur, D Rajnandg Dhamtar Bilaspur, Jagdalpu
Goa	Rice, coconut, cashew, arecanut, mango,	North Goa and South Goa; Pernem, Bicholim,	Kharif rice; perennial horticulture; rabi/	Small holdings, monsoon, plantation	1 LFC-distributed SHG drone	No state agricultural university in current ICAR SAU	Agriculture; Horticulture; Goa State Agricultural	Mapusa, Ponda, M and Pana

State	Major crops	Major agricultural districts	Major farming seasons	Major crop-protection challenges	Drone adoption information	Agricultural universities	Important agriculture departments	Major ag input/ wholesa market h
	banana, vegetables, spices	Bardez, Tiswadi, Salcete, Canacona	summer vegetables	pests, limited large-field mechanization	reported Jan-2026	list; Goa University and ICAR-CCARI Goa are relevant	Marketing Board; Goa SRLM	area trad hubs
Gujarat	Cotton, groundnut, wheat, bajra, castor, cumin, sesame, pulses, sugarcane, banana, mango, potato	Rajkot, Junagadh, Amreli, Bhavnagar, Jamnagar, Surendranagar, Banaskantha, Sabarkantha, Anand, Kheda, Bharuch, Surat, Kutch	Kharif, Rabi, summer/ irrigated	Drought/water stress, salinity, cotton pests, groundnut disease, heat	18 Namo Drone Didi SHGs Mar-2026; 58 LFC-distributed Jan-2026	Anand Agricultural University; Junagadh Agricultural University; Navsari AU; SDAU; Kamdhenu University	Agriculture; Horticulture; Gujarat State Agricultural Marketing Board; GULM	Unjha, Ra Gondal, Junagadh Deesa, Ar Ahmedal
Haryana	Wheat, rice, cotton, mustard, bajra, sugarcane, fodder, vegetables	Karnal, Kurukshetra, Ambala, Yamunanagar, Hisar, Sirsa, Fatehabad, Bhiwani, Jind, Kaithal, Rohtak, Rewari	Kharif, Rabi, summer fodder/ vegetables	Groundwater depletion, rice-wheat monocropping, residue, heat, resistance	22 Namo Drone Didi SHGs Mar-2026; 102 LFC-distributed Jan-2026	CCS Haryana Agricultural University; Maharana Pratap Horticultural University; LUVAS	Agriculture; Horticulture; Haryana State Agricultural Marketing Board; HSRLM	Karnal, H Sirsa, Fatehaba Kaithal, Kuruksh Ambala
Himachal Pradesh	Apple, maize, wheat, barley, rice, vegetables, stone fruits, seed potato	Shimla, Kullu, Kinnaur, Solan, Mandi, Sirmaur, Chamba, Kangra	Kharif/Rabi; temperate horticulture by elevation	Hail/frost, landslides, orchard pests/ disease, fragmented holdings	4 Namo Drone Didi SHGs Mar-2026; 4 LFC-distributed Jan-2026	CSK HP Krishi Vishvavidyalaya; Dr YS Parmar University of Horticulture & Forestry	Agriculture; Horticulture; HPMC/ marketing; HP SRLM	Shimla, S Parwano Mandi, K Bhattaku
Jharkhand	Rice, maize, pulses, oilseeds, wheat, vegetables, lac, horticulture	Ranchi, East/ West Singhbhum, Hazaribagh, Ramgarh, Dumka, Deoghar, Gumla, Lohardaga, Palamu, Latehar	Kharif dominant; rabi moisture/ irrigation dependent	Rainfed farming, drought, soil acidity, low irrigation, market access	1 Namo Drone Didi SHG Mar-2026; 15 LFC-distributed Jan-2026	Birsa Agricultural University	Agriculture; Horticulture; Jharkhand State Agricultural Marketing Board; JSLPS	Ranchi, Hazariba Jamshed Deoghar, Dumka
Karnataka	Rice, maize, ragi, pulses, cotton, sugarcane, groundnut, coffee, arecanut, coconut, grapes, banana, chilli	Belagavi, Dharwad, Haveri, Davanagere, Shivamogga, Tumakuru, Mandya, Mysuru, Raichur, Kalaburagi, Vijayapura, Kolar, Chikkaballapur, Kodagu	Kharif, Rabi, summer irrigated; plantation cycles	Drought, water stress, cotton/ chilli pests, coffee/ plantation diseases	82 Namo Drone Didi SHGs Mar-2026; 145 LFC-distributed Jan-2026	UAS Bengaluru, UAS Dharwad, UAS Raichur, UHS Bagalkot, KSNUAHS Shivamogga, KVAFSU	Agriculture; Horticulture; Karnataka Agricultural Marketing Board; KSRLM	Hubballi Belagavi, Davanag Raichur, Kalabura Vijayapu Bengalur Kolar
Kerala								

State	Major crops	Major agricultural districts	Major farming seasons	Major crop-protection challenges	Drone adoption information	Agricultural universities	Important agriculture departments	Major ag input/ wholesa market l
	Rice, coconut, rubber, pepper, cardamom, coffee, banana, vegetables, cashew	Palakkad, Thrissur, Alappuzha, Kottayam, Idukki, Wayanad, Kozhikode, Kannur, Kasaragod	Monsoon crops; rabi/ summer vegetables; perennial plantations	High rainfall/ floods/ landslides, fungal diseases, plantation pests, fragmented farms	2 Namo Drone Didi SHGs Mar-2026; 51 LFC-distributed Jan-2026	Kerala Agricultural University; KVASU; KUFOS	Agriculture; Horticulture; Kerala State Agricultural Marketing Board; Kudumbashree/ SRLM	Palakkad Thrissur, Kottayam Kochi/Alu Kozhikod Kannur, Kalpetta
Madhya Pradesh	Soybean, wheat, gram, maize, pulses, oilseeds, cotton, mustard, garlic, onion	Indore, Ujjain, Dewas, Sehore, Bhopal, Vidisha, Sagar, Raisen, Chhindwara, Jabalpur, Mandsaur, Neemuch, Ratlam, Khandwa, Khargone	Kharif soybean/ maize/ cotton; Rabi wheat/gram/ mustard	Soybean pests/ diseases, drought, weeds, storage and price volatility	34 Namo Drone Didi SHGs Mar-2026; 89 LFC-distributed Jan-2026	JNKVV Jabalpur; RVSKVV Gwalior; NDVSU	Agriculture; Horticulture; MP Mandi Board; SRLM	Indore, U Dewas, Mandsau Neemuch Ratlam, Sehore, B
Maharashtra	Cotton, soybean, sugarcane, tur, chickpea, wheat, onion, grapes, pomegranate, banana, citrus	Nashik, Ahmednagar, Pune, Solapur, Sangli, Kolhapur, Satara, Jalgaon, Dhule, Akola, Amravati, Yavatmal, Latur, Nanded, Nagpur, Wardha	Kharif, Rabi, summer irrigated; horticulture phenological cycles	Drought/water scarcity, cotton/pulse pests, grape/ pomegranate diseases, onion price volatility	30 Namo Drone Didi SHGs Mar-2026; 60 LFC-distributed Jan-2026	MPKV Rahuri; PDKV Akola; VNMKV Parbhani; DBSKKV Dapoli; MAFSU	Agriculture; Horticulture; Maharashtra State Agricultural Marketing Board; MAVIM/ SRLM	Nashik/ Lasalgao Pune, Ahmedna Solapur, S Jalgaon, A Latur
Manipur	Rice, maize, pulses, oilseeds, vegetables, pineapple, orange, ginger, turmeric	Imphal East/ West, Bishnupur, Thoubal, Kakching, Churachandpur, Ukhrul, Senapati	Kharif rice/ maize; rabi vegetables/ pulses	Hilly terrain, valley flooding, erosion, market access, fragmented farms	No state-specific Namo Drone Didi count in cited Mar-2026 release	Central Agricultural University, Imphal	Agriculture; Horticulture; Manipur State Agricultural Marketing; SRLM	Imphal, Thoubal, Kakching Assam gateways
Meghalaya	Rice, maize, potato, ginger, turmeric, pineapple, banana, citrus, vegetables	East/West Khasi Hills, Ri-Bhoi, East/West Garo Hills, West Jaintia Hills	Kharif and rabi vegetables/ potato; horticulture by elevation	Heavy rain, erosion, acidic soils, steep terrain, logistics	No state-specific Namo Drone Didi count in cited Mar-2026 release	No state agricultural university in current ICAR SAU list; ICAR/NEH and KVK network	Agriculture; Horticulture; Meghalaya State Agricultural Marketing Board; MSRLS	Shillong, Byrnihat Nongpoh Tura, Jow
Mizoram	Rice, maize, pulses, oilseeds, ginger, turmeric, chilli, vegetables, banana,	Aizawl, Lunglei, Champhai, Kolasib, Serchhip, Mamit, Lawngtlai, Saitual	Kharif dominant; horticulture by elevation	Steep terrain, erosion, fragmented/ shifting cultivation, logistics	No state-specific Namo Drone Didi count in cited Mar-2026 release	No state agricultural university in current ICAR SAU list; ICAR/NEH and KVK network	Agriculture; Horticulture; Mizoram State Agricultural Marketing; SRLM	Aizawl, Lunglei, Kolasib, Champha

State	Major crops	Major agricultural districts	Major farming seasons	Major crop-protection challenges	Drone adoption information	Agricultural universities	Important agriculture departments	Major ag input/ wholesa market l
	orange, pineapple							
Nagaland	Rice, maize, pulses, oilseeds, vegetables, pineapple, orange, ginger, turmeric, Naga chilli	Dimapur, Kohima, Mokokchung, Wokha, Mon, Tuensang, Zunheboto, Phek	Kharif dominant; rabi vegetables/ oilseeds	Hilly terrain, erosion, access, fragmented farms, post-harvest gaps	No state-specific Namo Drone Didi count in cited Mar-2026 release	Nagaland University; NE/ ICAR/KVK network	Agriculture; Horticulture; Nagaland State Agricultural Marketing; SRLM	Dimapur, Kohima, Mokokch
Odisha	Rice, pulses, groundnut, maize, cotton, sugarcane, vegetables, coconut, cashew, turmeric	Cuttack, Puri, Balasore, Mayurbhanj, Bargarh, Sambalpur, Kalahandi, Koraput, Ganjam, Dhenkanal, Angul	Kharif rice; rabi pulses/ oilseeds/ vegetables	Cyclones, floods/drought, rice pests, waterlogging, soil fertility	12 Namo Drone Didi SHGs Mar-2026; 16 LFC-distributed Jan-2026	OUAT Bhubaneswar	Agriculture; Horticulture; Odisha State Agricultural Marketing Board; Odisha Livelihoods Mission	Bhubane Cuttack, Balasore, Bargarh, Sambalp Berhamp Jeypore
Punjab	Rice, wheat, cotton, maize, mustard, sugarcane, vegetables, fodder	Ludhiana, Patiala, Sangrur, Moga, Bathinda, Mansa, Muktsar, Firozpur, Fazilka, Amritsar, Tarn Taran, Gurdaspur	Kharif rice/ cotton; Rabi wheat; summer maize/ vegetables	Groundwater depletion, monocropping, residue management, resistance, heat	23 Namo Drone Didi SHGs Mar-2026; 57 LFC-distributed Jan-2026	Punjab Agricultural University; GADVASU	Agriculture; Horticulture; Punjab Mandi Board; Punjab State Rural Livelihood Mission	Khanna, Ludhiana Moga, Sa Patiala, Bathinda Mansa, Muktsar, Fazilka
Rajasthan	Wheat, mustard, gram, bajra, barley, guar, cotton, cumin, coriander, isabgol	Sri Ganganagar, Hanumangarh, Alwar, Bharatpur, Kota, Baran, Bundi, Jhalawar, Nagaur, Bikaner, Jodhpur, Jaipur, Sikar	Kharif and Rabi; irrigated summer in command areas	Aridity, drought, salinity, heat, wind erosion, irrigation scarcity	19 Namo Drone Didi SHGs Mar-2026; 40 LFC-distributed Jan-2026	MPUAT Udaipur; SKRAU Bikaner; SKNAU Jobner; Agriculture Universities Kota/Jodhpur; RAUVS	Agriculture; Horticulture; Rajasthan State Agricultural Marketing Board; Rajeevika	Sri Gangana Hanuma Kota/Ran Mandi, A Jaipur, N Jodhpur, Bikaner
Sikkim	Large cardamom, ginger, turmeric, maize, rice, buckwheat, vegetables, orange	East, West, North, South and Pakyong districts	Kharif rainfed; rabi vegetables; perennial horticulture	Steep slopes, landslides, erosion, small farms, access	No state-specific Namo Drone Didi count in cited Mar-2026 release	No state agricultural university in current ICAR SAU list; ICAR/NEH network	Agriculture; Horticulture; Sikkim State Agricultural Marketing; SRLM	Gangtok, Singtam, Rangpo, Namchi; Siliguri s chain
Tamil Nadu	Rice, sugarcane, cotton, groundnut, maize, millets,	Thanjavur, Tiruvarur, Nagapattinam/ Mayiladuthurai, Tiruchirappalli, Erode,	Kuruvai/ Samba/ Thaladi rice; Rabi and summer crops	Water scarcity, cyclone/flood, rice/cotton pests, sugarcane disease, heat	17 Namo Drone Didi SHGs Mar-2026; 44 LFC-	TNAU Coimbatore; TANUVAS; TN Fisheries University	Agriculture; Horticulture; Tamil Nadu Agricultural Marketing; TNSRLM	Coimbato Erode, Sa Namakka Dindigul, Madurai, Thanjavu

State	Major crops	Major agricultural districts	Major farming seasons	Major crop-protection challenges	Drone adoption information	Agricultural universities	Important agriculture departments	Major ag input/ wholesa market l
	pulses, banana, coconut, turmeric, vegetables, mango	Coimbatore, Salem, Namakkal, Dindigul, Theni, Tiruppur, Villupuram, Krishnagiri			distributed Jan-2026			Villupura Chennai/ Koyambe
Telangana	Rice, cotton, maize, soybean, red gram, green gram, chilli, turmeric, horticulture	Nizamabad, Kamareddy, Karimnagar, Jagtial, Peddapalli, Warangal/ Hanamkonda, Khammam, Suryapet, Nalgonda, Adilabad/ Nirmal, Sangareddy	Kharif and Rabi; irrigated summer paddy in command areas	Cotton pests, paddy pests/ diseases, drought/heat, chilli pests, water/price volatility	72 Namo Drone Didi SHGs Mar-2026; 81 LFC-distributed Jan-2026	PJTSAU; Sri Konda Laxman Telangana State Horticultural University; PVNRTVU	Agriculture; Horticulture; Telangana State Agricultural Marketing; SERP	Hyderab Waranga Nizamab Karimna Khamma Suryapet Nalgonda Adilabad
Uttar Pradesh	Rice, wheat, sugarcane, potato, maize, pulses, mustard, vegetables, mango	Lakhimpur Kheri, Sitapur, Hardoi, Shahjahanpur, Bareilly, Meerut, Muzaffarnagar, Bijnor, Agra, Farrukhabad, Kannauj, Aligarh, Prayagraj, Varanasi, Gorakhpur	Kharif, Rabi, Zaid; sugarcane/ horticulture longer cycles	Flood/drought, sugarcane pests, rice-wheat pressure, potato blight, groundwater	32 Namo Drone Didi SHGs Mar-2026; 128 LFC-distributed Jan-2026	CSAUA&T Kanpur; SVPUAT Meerut; NDUAT Ayodhya; BUAT Banda	Agriculture; Horticulture; UP Mandi Parishad; UP State Rural Livelihood Mission	Kanpur, A Lucknow Meerut, Muzaffar Bareilly, Varanasi Farrukha
Uttarakhand	Rice, wheat, maize, millets, sugarcane, vegetables, apple, pear, citrus, spices	Udham Singh Nagar, Nainital, Haridwar, Dehradun, Pauri, Almora, Tehri, Uttarkashi, Chamoli	Kharif/Rabi; hill horticulture by elevation	Hills, landslides, rain variability, fragmented farms, wildlife damage	3 Namo Drone Didi SHGs Mar-2026; 3 LFC-distributed Jan-2026	GBPUAT Pantnagar; VCSG Uttarakhand University of Horticulture & Forestry	Agriculture; Horticulture; Uttarakhand Agricultural Produce Marketing Board; SRLM	Rudrapu Kashipur Haldwan Haridwa Dehradu Pantnaga
West Bengal	Rice, potato, jute, wheat, maize, mustard, vegetables, tea, mango, litchi, banana, pineapple	Bardhaman, Nadia, Murshidabad, Hooghly, North/ South 24 Parganas, Malda, Jalpaiguri, Uttar Dinajpur, Cooch Behar, Bankura	Aman/Aus/ Boro rice; rabi/ summer crops; tea/ horticulture	Flood/cyclone/ coastal salinity, humidity diseases, rice/ potato pests, fragmented farms	7 Namo Drone Didi SHGs Mar-2026; 15 LFC-distributed Jan-2026	BCKV Mohanpur; Uttar Banga Krishi Viswavidyalaya; WBUAFS	Agriculture; Horticulture; West Bengal State Agricultural Marketing Board; Anandadhara/ SRLM	Bardham Kalyani/ Siliguri, Hooghly, Kolkata/ Howrah, Behar

Source: `State_Wise_Agricultural_Information_Database.xlsx` · Google Drive file id `1TmaPvl49WOO1kuihmu3Uj9jTwicJg6wO` · folder “5. State wise Agricultural Information”

6. Government Schemes and Subsidies

agricultural drone subsidies and government schemes — central and state schemes, farmer subsidies, FPO schemes, custom hiring centres, drone entrepreneur and drone pilot/operator schemes, women farmer initiatives

In this section: Agriculture drone subsidies, Central government schemes, Custom Hiring Centres, Drone entrepreneur schemes, Drone pilot..operator schemes, FPO schemes, Farmer subsidies, Government drone schemes, State government schemes, Women farmer drone initiatives

Agriculture drone subsidies

Agricultural drone subsidies

Agricultural drone subsidies in India in 2026 represent one of the most ambitious rural technology adoption programs, carefully structured under schemes like the Kisan Drone Yojana, the Namo Drone Didi Scheme and institutional support initiatives for soil testing and precision farming, all designed to make drones accessible to smallholders, women's groups and Farmer Producer Organisations (FPOs). These subsidies are not token gestures but substantial financial interventions: small and marginal farmers, SC/ST communities and women farmers receive 50% subsidy up to ₹6 lakh, general category farmers are eligible for 40% subsidy up to ₹4 lakh, while FPOs and Custom Hiring Centres (CHCs) benefit from 75% subsidy up to ₹7.5 lakh, enabling them to rent drones to other farmers at affordable rates. The Namo Drone Didi program is particularly transformative, targeting 15,000 women SelfHelp Groups with 80% subsidy up to ₹8 lakh per drone, bundled with 15day training, oneyear insurance and two years of maintenance, ensuring that women operators not only access technology but also generate steady monthly incomes of ₹15,000–20,000 through spraying services. Institutional subsidies are even higher: ICAR, KVKs and State Agricultural Universities receive 100% subsidy up to ₹10 lakh for drones used in soil testing and crop health monitoring, while FPOs and SHGs receive 75–80% support for similar applications.

The impact of these subsidies is visible in the field: drones can spray one acre in 7–10 minutes compared to 2–4 hours manually, save 25–40% pesticide usage and reduce water consumption by nearly tenfold compared to knapsack sprayers. Farmers benefit from reduced chemical drift, improved canopy penetration and safer working conditions, while CHCs and SHGs generate rural income streams by renting drones at ₹5,000–10,000 per day. Application processes are streamlined through agrimachinery.nic.in and state portals, requiring Aadhaar, land records, caste certificates, SHG/FPO registration and bank details, with subsidies disbursed directly to vendors or farmer accounts. Challenges remain annual maintenance costs of ₹50,000–1 lakh, training gaps in DGCAapproved certification and uneven awareness across states but overall, these subsidies are reshaping rural economies by embedding drones into everyday farming.

In essence, India's agricultural drone subsidies in 2026 are not just financial incentives but a policy revolution: they democratize access to cuttingedge technology, empower women's collectives, strengthen FPOs and reduce environmental externalities by cutting chemical drift and runoff. Every subsidized drone becomes more than a machine, it is a catalyst for rural innovation, efficiency and resilience, proving that subsidies are not merely about affordability but about transforming agriculture into a precisiondriven, sustainable enterprise for the decades ahead.

Source: `Agriculture drone subsidies.docx` · Google Drive file id `1XCCKRa1CDMEOnsoVWQxBlzwixDn0B7vO` · folder "6. Goverment Schemes & Subsidies"

Central government schemes

Central government schemes

Central government agricultural drone schemes in India in 2026 are a consolidated policy framework under the Ministry of Agriculture & Farmers Welfare that directly integrates drones into farming practices through subsidies, training, insurance and institutional support, making them accessible to smallholders, women's SelfHelp Groups (SHGs), Farmer Producer Organisations (FPOs) and agricultural universities, the flagship Kisan

Drone Yojana, launched in 2022 and expanded in 2026, provides 40–50% subsidy for individual farmers (₹4–6 lakh depending on category) and 75% subsidy for FPOs and Custom Hiring Centres (CHCs) (up to ₹7.5 lakh), enabling both ownership and rental services, while the Namo Drone Didi Scheme, introduced in

2023, specifically empowers women's SHGs with 80% subsidy up to ₹8 lakh per drone, bundled with 15day training, oneyear insurance and two years of maintenance, ensuring that women operators not only access technology but also generate steady incomes of ₹15,000–20,000 per month through spraying services, additionally, the Drone Soil Testing Subsidy backed by ICAR and ISRO provides 100% subsidy up to ₹10 lakh for ICAR, Krishi Vigyan Kendras and State Agricultural Universities, while FPOs and SHGs receive 75–80% support, promoting the use of multispectral drones for soil health mapping and nutrient management, which reduces analysis time from weeks to hours with less than 10% error compared to lab tests, collectively, these schemes deliver multiple benefits, drones can spray one acre in 7–10 minutes compared to 2–4 hours manually, save 25–40% pesticide usage, reduce water consumption by nearly tenfold and eliminate health hazards associated with manual spraying, while CHCs and SHGs generate rural income streams by renting drones at ₹5,000–10,000 per day, the application process is streamlined through agrimachinery.nic.in and state portals, requiring Aadhaar, land records, caste certificates, SHG/FPO registration and bank details, with subsidies disbursed directly to vendors or farmer accounts and GST on agricultural drones reduced to 5% to lower upfront costs, challenges remain in terms of training gaps (DGCAapproved certification is mandatory), annual maintenance costs of ₹50,000–1 lakh and uneven awareness across states but overall these central government schemes represent a policy revolution, embedding drones into everyday farming practices, empowering women's collectives, strengthening FPOs and reducing environmental externalities by cutting chemical drift and runoff, ensuring that every subsidized drone is not merely a machine but a catalyst for rural innovation, efficiency and resilience, positioning India's agricultural future as precisiondriven, inclusive and sustainable.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in), ICAR policy circulars (2025–2026), government press releases on Kisan Drone Yojana and Namo Drone Didi (2023–2026), ISRO–ICAR collaborative reports on drone soil testing and Matribhumi Samachar (June 2026).

Source: `Central government schemes.docx` · Google Drive file id `1Sbc1CQMo7hP9itMdrRPwQpIJmySBTVHJ` · folder "6. Goverment Schemes & Subsidies"

Custom Hiring Centres

Custom Hiring Centres (CHCs) in India in 2026 are a cornerstone of the government's agricultural mechanisation policy, designed to provide small and marginal farmers access to expensive machinery tractors, harvesters, drones and soil testing kits on a rental basis, thereby reducing input costs and democratizing technology adoption, under the SubMission on Agricultural Mechanisation (SMAM), CHCs are established at village and block levels with 40–80% subsidy support, depending on farmer category and are often managed by Farmer Producer Organisations (FPOs), SelfHelp Groups (SHGs) or cooperatives, ensuring collective ownership and service delivery, the subsidy norms are structured so that individual farmers receive 40–50% subsidy, while FPOs and CHCs themselves receive up to 75% subsidy, making them financially viable service hubs, CHCs are particularly important in drone adoption under the Kisan Drone Yojana, CHCs receive 75% subsidy up to ₹7.5 lakh per drone, enabling them to rent drones to farmers at ₹5,000–10,000 per day, which is far cheaper than individual ownership, while women's SHGs under the Namo Drone Didi Scheme receive 80% subsidy up to ₹8 lakh, ensuring genderinclusive access, beyond drones, CHCs house tractors, power tillers, rotavators, seed drills and harvesters, with rental rates fixed by state governments to ensure affordability, for example ₹400–600 per hour for tractors and ₹1,500–2,000 per hour for harvesters, thereby reducing labour costs and increasing efficiency, the benefits of CHCs are multifold, farmers save 20–30% on input costs, increase cropping intensity by accessing machinery on time and reduce drudgery, while CHCs themselves generate rural employment by hiring operators and technicians, state governments have localized CHC implementation, Uttar Pradesh operates CHCs through the Agridarshan portal, Maharashtra integrates them into MahaDBT Andhra Pradesh links them to Rythu Bharosa Kendras and Telangana ties them to Rythu Bandhu, each ensuring that subsidies are disbursed directly to FPOs and SHGs, challenges remain in terms of maintenance costs (₹50,000–1 lakh annually for drones and harvesters), uneven awareness across districts and the need for DGCAapproved certification for drone operators but overall CHCs in 2026 represent a policy revolution, embedding mechanisation into everyday farming practices, empowering collectives, reducing environmental externalities

by cutting chemical drift and runoff and ensuring that every subsidized machine is not merely a tool but a catalyst for rural innovation, efficiency and resilience, positioning India's agricultural future as precisiondriven, inclusive and sustainable.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in), Press Information Bureau releases on SMAM and CHCs (2025–2026), ICAR circulars on drone subsidies and state agriculture department portals (Agridarshan, MahaDBT, Rythu Bharosa, Rythu Bandhu).

Source: `Custom Hiring Centres.docx` · Google Drive file id `1yDhFOYS6XpPfwQjJm_55lbqOINDWXqeY` · folder "6. Goverment Schemes & Subsidies"

Drone entrepreneur schemes

Drone entrepreneur schemes

Drone entrepreneur schemes in India in 2026 are central government initiatives designed to create a new class of rural service providers who own and operate drones for agricultural purposes, with the Kisan Drone Yojana and the Namo Drone Didi Scheme forming the backbone of this effort, under the Kisan Drone Yojana, subsidies are provided at 40–50% for individual farmers (₹4–6 lakh depending on category) and 75% for Farmer Producer Organisations and Custom Hiring Centres (up to ₹7.5 lakh), enabling entrepreneurs to establish rental services where drones are hired out at ₹5,000–10,000 per day, while the Namo Drone Didi program specifically empowers women's SelfHelp Groups with 80% subsidy up to ₹8 lakh per drone kit, bundled with 15day DGCAapproved pilot training, oneyear insurance and two years of maintenance, ensuring that women entrepreneurs not only access technology but also generate steady incomes of ₹15,000–20,000 per month through spraying services, financing support is provided through the Agriculture Infrastructure Fund, which covers the remaining 20% cost with loans at 3% interest subvention, thereby lowering entry barriers for rural entrepreneurs, beyond spraying, drone entrepreneurs are encouraged to expand into soil testing, crop health mapping and precision nutrient management, with ICAR–ISRO backed schemes offering 100% subsidy for institutions and 75–80% for FPOs and SHGs, enabling entrepreneurs to diversify services, the government also provides monthly honorariums under Namo Drone Didi-₹15,000 for Drone Didis and ₹10,000 for assistantensuring financial stability during the initial phase, statewise deployment has been significant, with Andhra Pradesh, Karnataka, Maharashtra, Punjab, Tamil Nadu, Telangana, Gujarat, Madhya Pradesh and Rajasthan all reporting hundreds of SHGs trained and equipped under the scheme, while awareness campaigns and demonstration flights are conducted through Krishi Vigyan Kendras and agricultural universities, the benefits of these schemes are multifold drones can spray one acre in 7–10 minutes compared to 2–4 hours manually, save 25–40% pesticide usage, reduce water consumption by nearly tenfold and eliminate health hazards associated with manual spraying, while entrepreneurs generate new income streams and rural employment opportunities, challenges remain in terms of annual maintenance costs of ₹50,000–1 lakh, the need for DGCA licensing and certification and uneven awareness across districts but overall drone entrepreneur schemes in 2026 represent a policy revolution, embedding entrepreneurship into everyday farming practices, empowering women's collectives, strengthening FPOs and reducing environmental externalities, ensuring that every subsidized drone is not merely a machine but a catalyst for rural innovation, efficiency and resilience, positioning India's agricultural future as precisiondriven, inclusive and sustainable.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in, agri.dac.gov.in), Press Information Bureau (PIB Delhi releases, 2023–2026), Kisan Drone Yojana and Namo Drone Didi, Agriculture Infrastructure Fund guidelines (2025–2026)

Source: `Drone entrepreneur schemes.docx` · Google Drive file id `1pGdAfrpOyNCr8WC1zsTwUxNjctGoDLak` · folder "6. Goverment Schemes & Subsidies"

Drone pilot..operator schemes

Drone pilot/operator schemes

Drone pilot/operator schemes in India in 2026 are structured to build a certified workforce capable of safely and effectively operating agricultural drones, with the Directorate General of Civil Aviation (DGCA) and the Ministry of Agriculture & Farmers Welfare jointly overseeing training, licensing and subsidy support. Under

the Kisan Drone Yojana and Namo Drone Didi Scheme, every drone entrepreneur or SHG beneficiary must undergo DGCAapproved Remote Pilot Training at designated Remote Pilot Training Organisations (RPTOs). The training program typically lasts 15 days, covering modules on drone assembly, flight operations, precision spraying, soil mapping, safety protocols and maintenance. Upon completion, operators receive a Remote Pilot Certificate, which is mandatory for commercial drone use in agriculture.

The government subsidizes training costs through the Agriculture Infrastructure Fund and SMAM (SubMission on Agricultural Mechanisation), ensuring that smallholders, women and SC/ST farmers can access certification at minimal expense. For women SHGs under Namo Drone Didi, training is bundled into the subsidy package, along with insurance and maintenance, so that Drone Didis and their assistants are fully prepared to operate drones professionally. Operators are also eligible for monthly honorariums ₹15,000 for Drone Didis and ₹10,000 for assistants during the initial deployment phase, ensuring financial stability while they build service networks.

State governments complement these central efforts: Andhra Pradesh and Telangana run pilot training through Rythu Bharosa Kendras and PJTSAU, Maharashtra integrates training into its MahaDBT portal and Uttar Pradesh uses Agridarshan to register operators. Training centers are often linked to Krishi Vigyan Kendras (KVKs) and agricultural universities, ensuring regional accessibility. Certified operators then provide services such as pesticide spraying, nanourea application, soil health mapping and rental operations through Custom Hiring Centres (CHCs) and FPOs.

The impact of these schemes is significant: certified drone pilots can spray one acre in 7–10 minutes compared to 2–4 hours manually, reduce pesticide use by 25–40%, cut water consumption tenfold and eliminate health hazards from manual spraying. For operators, this translates into steady income streams of ₹15,000–20,000 per month, plus seasonal rental earnings. Challenges remain in terms of annual maintenance costs (₹50,000–1 lakh), the need for continuous skill upgrades and uneven awareness across districts but the government is addressing these through awareness campaigns, demonstration flights and integration with FPO schemes.

Drone pilot/operator schemes in India in 2026 represent a policy revolution in skill development, embedding certified drone operators into the agricultural ecosystem. By combining subsidies, training, licensing and honorariums, these schemes ensure that drone operators are not just machine handlers but entrepreneurs and service providers, catalyzing rural innovation, efficiency and resilience and positioning India’s agricultural future as precisiondriven, inclusive and sustainable.

Genuine sources of information: Directorate General of Civil Aviation (dgca.gov.in), Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in, agri.dac.gov.in).

Source: `Drone pilot..operator schemes.docx` · Google Drive file id `1MTHH5y7eu96lCWsD8HhQmPcVHrAOEDIf` · folder “6. Goverment Schemes & Subsidies”

FPO schemes

FPO Schemes

Farmer Producer Organisation (FPO) schemes in India in 2026 are centrally funded but implemented statewise, with each state tailoring support to local crops, farmer groups and institutions. The central scheme provides up to ₹18 lakh per FPO for management, ₹2,000 per farmer equity grant (capped at ₹15 lakh per FPO) and credit guarantee cover up to ₹2 crore, while states add their own subsidies, training and market linkages.

Central Implementation

- Scheme: Formation & Promotion of 10,000 FPOs (launched 2020, budget ₹6,865 crore).
- Support: ₹18 lakh per FPO for 3 years, equity grant ₹2,000 per farmer (max ₹15 lakh), credit guarantee up to ₹2 crore.
- Progress: By Dec 2025, 10,000 FPOs registered, ₹430.77 crore equity grants disbursed, ₹662.71 crore credit guarantees issued.

StateWise Implementation

Uttar Pradesh

- Portal: Agridarshan.
- Focus crops: paddy, wheat, sugarcane.
- FPOs receive central equity grants plus state marketing support.
- Drone subsidies: 75% under Kisan Drone Yojana for collective spraying.

Maharashtra

- Portal: MahaDBT, program: MahaFPO.
- Focus crops: cotton, sugarcane, horticulture.
- Women SHGFPOs get 80% drone subsidy under Namo Drone Didi.
- State adds cold storage and warehouse subsidies.

Andhra Pradesh

- Implemented via Rythu Bharosa Kendras.
- Focus crops: chilli, banana, paddy.
- State adds demonstration projects and DGCA pilot training.
- Soil testing drones subsidized at 100% for institutions, 75% for FPOs.

Telangana

- Linked to Rythu Bandhu.
- Focus crops: cotton, maize, paddy.
- Adds direct cash support for collective input purchases.
- Awareness campaigns run by PJTSAU.

Karnataka

- Department of Agriculture promotes FPOs in ragi, maize, horticulture.
- FPOs linked to SHGs, ensuring women's participation.
- Drone spraying subsidized at 75% for FPOs.

Tamil Nadu

- Integrated into Precision Farming Initiative.
- Focus crops: rice, sugarcane, banana.
- FPOs linked to eNAM for collective marketing.

Punjab & Haryana

- Focus crops: paddy, cotton.
- Subsidies routed through cooperative societies.
- Emphasis on reducing pesticide drift via drones.

Kerala

- FPOs in paddy and spices.
- Cooperative societies converted into FPOs.
- Subsidies for drone spraying in waterlogged fields.

Gujarat

- Integrated into Krishi Mahotsav.
- Focus crops: cotton, groundnut.
- FPOs actively hedge commodities on NCDEX (16,013 MT traded in June 2026).

Madhya Pradesh

- Focus crops: wheat, soybean.
- Demonstration projects run via universities.
- FPOs hedge commodities like castor, guar seed, turmeric on NCDEX (12,017 MT traded in June 2026).

Rajasthan

- Focus crops: millet, mustard.
- FPOs hedge guar seed and rainfed crops (5,820 MT traded in June 2026).

West Bengal

- Focus crops: rice, jute.
- FPOs subsidized for drone spraying in delta regions.
- Collective marketing through cooperatives.

📊 Benefits of FPO Schemes

- Collective bargaining: Input costs reduced 10–20%.
- Market access: Farmgate prices increased 15–30%.
- Credit access: Institutional loans guaranteed up to ₹2 crore.
- Technology adoption: Drones, soil testing kits, mechanisation pooled.
- Commodity hedging: FPOs trade on NCDEX, reducing price volatility.

Conclusion

FPO schemes in 2026 are both centralized and statespecific, ensuring that collective farming is embedded into India's agricultural landscape. By combining central equity grants, credit guarantees and drone subsidies with statelevel mechanisation, training and market support, FPOs have become catalysts for rural innovation, efficiency and resilience. They reduce costs, increase incomes and democratize access to technology, positioning Indian agriculture as precisiondriven, inclusive and sustainable.

Sources: Press Information Bureau (Feb 2026), TataCornell Institute report (2026), NCDEX FPO trading data (June 2026).

Source: `FPO schemes.docx` · Google Drive file id `1te3-6-AD7EOP7YWI7VBYf3G7xpBMqQ-Q` · folder "6. Goverment Schemes & Subsidies"

Farmer subsidies

Farmer subsidies

Farmer subsidies in India in 2026 represent one of the most comprehensive welfare and modernization frameworks in the world, combining direct income support, input cost reduction, mechanisation incentives and technology adoption programs under both central and state governments, with schemes like PMKisan Samman Nidhi, the Kisan Drone Yojana, the Namo Drone Didi Scheme, fertilizer and seed subsidies, crop insurance under PM Fasal Bima Yojana and statespecific mechanisation programs forming the backbone of this support system, PMKisan continues to provide ₹6,000 annually in three installments directly to farmers' bank accounts, ensuring liquidity for smallholders, while input subsidies reduce the cost of fertilizers, seeds andelectricity for irrigation, with urea still heavily subsidized to keep prices affordable, mechanisation subsidies under SMAM (SubMission on Agricultural Mechanisation) cover 40–80% of equipment costs, including tractors, harvesters and drones, with special provisions for SC/ST, women andsmall/marginal

farmers, while the Kisan Drone Yojana and Namo Drone Didi specifically democratize access to precision spraying and soil testing by offering 40–80% subsidies up to ₹4–8 lakh per drone, bundled with training, insurance and maintenance, thereby reducing pesticide use by 25–40%, water consumption tenfold and health hazards from manual spraying, crop insurance under PMFBY provides coverage against natural calamities, pests and diseases, with premiums capped at 2% for kharif crops, 1.5% for rabi crops and5% for horticulture, ensuring risk mitigation for millions of farmers, state governments complement these central schemes with localized programs—for example, Uttar Pradesh's Agridarshan portal, Maharashtra's MahaDBT, Andhra Pradesh's Rythu Bharosa Kendras and Telangana's Rythu Bandhu—each offering subsidies on machinery, seeds and drones tailored to regional crops like paddy, cotton, sugarcane andmillets, collectively, these subsidies not only reduce production costs but also create new income streams, as Custom Hiring Centres and SHGs rent subsidized equipment at affordable rates, generating rural employment and service models, challenges remain in terms of awareness gaps, uneven access across states and maintenance costs of advanced machinery like drones but overall farmer subsidies in India in 2026 represent a policy revolution, embedding financial support, risk protection and technology adoption into everyday farming practices, ensuring that subsidies are not merely welfare transfers but catalysts for rural innovation, efficiency and resilience, positioning Indian agriculture as precisiondriven, inclusive and sustainable for decades ahead.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in, pmkisan.gov.in), ICAR policy circulars (2025–2026), government press releases on PMKisan, PMFBY, Kisan Drone Yojana andNamo Drone Didi (2023–2026), ISRO–ICAR collaborative reports on drone soil testing andstate agriculture department portals (MahaDBT, Agridarshan, Rythu Bandhu, Rythu Bharosa).

Source: `Farmer subsidies.docx` · Google Drive file id `1ssMsb-sEYYtSqIwbB7E4GkrSCH75RQcB` · folder "6. Goverment Schemes & Subsidies"

Government drone schemes

Government drone schemes

Government agricultural drone schemes in India in 2026 are designed as a transformative policy framework to accelerate the adoption of precision farming technologies, reduce input costs and empower rural communities, with flagship programs such as the Kisan Drone Yojana, the Namo Drone Didi Scheme and ICAR–ISRO backed soil testing initiatives forming the backbone of this effort, under the Kisan Drone Yojana, subsidies are provided at 40–50% for individual farmers (₹4–6 lakh depending on category) and 75% for Farmer Producer Organisations and Custom Hiring Centres (up to ₹7.5 lakh), enabling both ownership and rental services, while the Namo Drone Didi program specifically empowers women's SelfHelp Groups with 80% subsidy up to ₹8 lakh per drone, bundled with training, insurance and maintenance, ensuring that women operators not only access technology but also generate steady incomes through spraying services, institutional schemes extend support further, with ICAR, Krishi Vigyan Kendras and State Agricultural Universities receiving 100% subsidy up to ₹10 lakh for drones used in soil testing and crop health monitoring, while FPOs and SHGs receive 75–80% support for similar applications, thereby expanding drone usage beyond spraying into soil health mapping and precision nutrient management, the benefits of these schemes are multifold—drones can spray one acre in 7–10 minutes compared to 2–4 hours manually, save 25–40% pesticide usage, reduce water consumption by nearly tenfold and eliminate health hazards associated with manual spraying, while CHCs and SHGs generate rural income streams by renting drones at ₹5,000–10,000 per day, application processes are streamlined through agrimachinery.nic.in and state portals, requiring Aadhaar, land records, caste certificates, SHG/FPO registration and bank details, with subsidies disbursed directly to vendors or farmer accounts and GST on agricultural drones reduced to 5% to lower upfront costs, challenges remain in terms of training gaps, annual maintenance costs of ₹50,000–1 lakh and uneven awareness across states but overall these government schemes represent a policy revolution, embedding drones into everyday farming practices, empowering women's collectives, strengthening FPOs and reducing environmental externalities by cutting chemical drift and runoff, ensuring that every subsidized drone is not merely a machine but a catalyst for rural innovation, efficiency and resilience, positioning India's agricultural future as precisiondriven, inclusive and sustainable.

Source: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in), ICAR policy circulars and government press releases on Kisan Drone Yojana and Namo Drone Didi (2023–2026).

Source: `Government drone schemes.docx` · Google Drive file id `17Vm-KDxk4E5zjHW93e5EkmacWJovlyC4` · folder “6. Goverment Schemes & Subsidies”

State government schemes

State government schemes

Uttar Pradesh

Through the Agridarshan portal, UP offers 50% subsidy up to ₹6 lakh for small/marginal farmers, 40% subsidy up to ₹4 lakh for general farmers and 75% subsidy up to ₹7.5 lakh for FPOs/CHCs. Rental services are promoted at ₹5,000–10,000/day, with drones used widely in paddy and wheat spraying.

Maharashtra

Via the MahaDBT portal, Maharashtra integrates drone subsidies into its mechanisation program. Women SHGs under Namo Drone Didi receive 80% subsidy up to ₹8 lakh, plus training, insurance and maintenance. CHCs are incentivized to establish drone rental hubs, focusing on cotton and sugarcane spraying.

Andhra Pradesh

AP aligns with SMAM guidelines but adds support through Rythu Bharosa Kendras. Demonstration projects, DGCAapproved pilot training and subsidies for drones spraying nanourea and pesticides are emphasized. Drones are used in chilli, banana and paddy fields.

Karnataka

The Department of Agriculture subsidizes drones for precision spraying, linking SHGs to income generation models. Focus crops include ragi, maize and horticultural produce. Training programs are run through state agricultural universities.

Tamil Nadu

Integrated into the Precision Farming Initiative, TN subsidizes drones for soil testing and crop health monitoring. Farmers receive support for DGCA pilot licensing, with drones used in rice, sugarcane and banana cultivation.

Punjab & Haryana

Both states emphasize drones for pesticide spraying in paddy and cotton. Subsidies are routed through cooperative societies and FPOs. Demonstration flights are conducted to reduce pesticide drift and groundwater contamination.

Telangana

Through Rythu Bandhu, Telangana supports drone adoption by FPOs and SHGs. Subsidies mirror central norms, with awareness campaigns run by PJTSAU (state agricultural university). Drones are used in cotton, maize and paddy.

Kerala

Kerala pilots drone spraying in paddy fields under its mechanisation drive, offering subsidies to cooperative societies and SHGs. Focus is on reducing labour costs in waterlogged fields.

Gujarat

Drone subsidies are integrated into Krishi Mahotsav programs, focusing on cotton and groundnut spraying. FPOs receive 75% subsidy and SHGs 80%, with emphasis on precision nutrient application.

Madhya Pradesh

Through its farm mechanisation scheme, MP subsidizes drones for wheat and soybean farmers. Demonstration projects are run in collaboration with agricultural universities.

Rajasthan

Rajasthan emphasizes drone spraying in arid zones, subsidizing drones for millet and mustard crops. Rental hubs are promoted to serve smallholders in desert districts.

West Bengal

WB adopts drones for rice spraying under its mechanisation program, offering subsidies to FPOs and SHGs. Demonstrations are conducted in Sundarbans and delta regions to reduce pesticide runoff.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in), MahaDBT Portal (Government of Maharashtra, 2026), Agridarshan Portal (Government of Uttar Pradesh, 2026), ICAR–ISRO collaborative reports (2025–2026) and state agriculture department press releases (Andhra Pradesh, Karnataka, Tamil Nadu, Punjab, Telangana, Kerala, Gujarat, Madhya Pradesh, Rajasthan, West Bengal, 2026).

Source: `State government schemes.docx` · Google Drive file id `1yEPTKZs28S8l8O-w6AFj9aNs-ISTXEQx` · folder "6. Goverment Schemes & Subsidies"

Women farmer drone initiatives

Women farmer drone initiatives

Women farmer drone initiatives in India in 2026 are among the most transformative agricultural empowerment programs, designed to integrate gender inclusivity into precision farming by providing subsidies, training, insurance and financing specifically for women's SelfHelp Groups (SHGs). The flagship initiative is the Namo Drone Didi Scheme, approved as a Central Sector Scheme with an outlay of ₹1,261 crore for 2023–2026, which provides 80% subsidy up to ₹8 lakh per drone kit to women SHGs. Each kit includes a drone with spray assembly, four spare batteries, propellers, nozzles, a dual fast charger, 15day DGCAapproved pilot training, oneyear insurance and two years of maintenance support. The remaining 20% cost is financed through the Agriculture Infrastructure Fund (AIF) with a 3% interest subvention loan, ensuring affordability. To strengthen entrepreneurship, the scheme provides a monthly honorarium of ₹15,000 for Drone Didis and ₹10,000 for assistants, guaranteeing stable income during the initial phase.

Deployment has been statewise and extensive: Andhra Pradesh trained and equipped 96 SHGs, Karnataka 82, Maharashtra 30, Punjab 23, Tamil Nadu 17, Telangana 16, Gujarat 18, Madhya Pradesh 34 and Rajasthan 19, with smaller numbers in other states. These womenled drone units are now offering spraying services for pesticides, nanourea and fertilizers, earning ₹15,000–20,000 per month while simultaneously reducing farmers' costs. Field reports show that drone spraying saves 25–40% pesticide use, reduces water consumption by nearly tenfold and eliminates health hazards associated with manual spraying. Beyond spraying, women SHGs are also expanding into soil testing and crop health mapping, supported by ICAR–ISRO collaborations that subsidize drones for nutrient management, enabling women entrepreneurs to diversify services.

The broader impact of these initiatives is profound: they empower women farmers with technology ownership, create new rural employment opportunities and strengthen collective farming models. By embedding women into the mechanisation ecosystem, the government ensures that gender inclusivity is not symbolic but structural, with women SHGs becoming service providers, entrepreneurs and leaders in precision agriculture. Challenges remain in terms of annual maintenance costs (₹50,000–1 lakh), the need for DGCA licensing and certification and uneven awareness across districts but awareness campaigns and demonstration flights through Krishi Vigyan Kendras and agricultural universities are bridging these gaps.

In conclusion, women farmer drone initiatives in India in 2026—anchored by Namo Drone Didi and supported by central and state programs—represent a policy revolution. They democratize access to drones, empower women's collectives, reduce environmental externalities and embed entrepreneurship into everyday farming practices. Every subsidized drone in the hands of a woman farmer is not merely a machine but a catalyst for rural innovation, efficiency and resilience, positioning India's agricultural future as precisiondriven, inclusive and sustainable.

Sources of information: Ministry of Agriculture & Farmers Welfare (agrimachinery.nic.in, agri.dac.gov.in), Press Information Bureau (PIB Delhi releases, 2023–2026), official circulars on Namo Drone Didi and Kisan Drone Yojana.

Source: `Women farmer drone initiatives.docx` · Google Drive file id `19W7Hd-DFbY7DZ6tgctAFNlvFUeZn1NM6` · folder "6. Goverment Schemes & Subsidies"

7. Drone Regulations

Indian drone regulations — DGCA rules, drone categories, pilot requirements, remote pilot certification, drone registration, Digital Sky, no-fly zones, agricultural spraying requirements and insurance

In this section: Agricultural spraying requirements, DGCA rules, Digital Sky, Drone categories, Drone registration, Insurance, No-flyrestricted zones, Pilot requirements, Remote pilot certification

Agricultural spraying requirements

Agricultural spraying requirements

Agricultural spraying with drones in India is governed by a strict framework laid down by the Directorate General of Civil Aviation (DGCA) under the Drone Rules, 2021 and subsequent amendments, along with the Central Insecticides Board & Registration Committee (CIB&RC) which regulates pesticide use. The purpose of these requirements is to ensure that aerial spraying is safe for farmers, compliant with aviation law and environmentally responsible. To begin with, every spray drone must undergo type certification by DGCA to verify its design, payload capacity, nozzle system and safety features. Only typecertified drones can be registered on the Digital Sky Platform, where they are assigned a Unique Identification Number (UIN). Operators must also hold a valid Remote Pilot Certificate (RPC) issued by a DGCAapproved Remote Pilot Training Organisation (RPTO). This ensures that pilots are trained in airspace rules, meteorology, emergency procedures and safe spraying practices.

Chemical use is tightly controlled. Only formulations approved by CIB&RC for aerial application can be sprayed. The Standard Operating Procedures (SOPs) specify nozzle calibration, droplet size, spray volume, buffer zones near habitations and weather thresholds. For example, spraying is prohibited during high winds, heavy rain or extreme heat to prevent drift and environmental contamination. Operators must wear protective gear and maintain detailed records of spray operations, including date, crop, chemical used and area covered.

Operational rules also require drones to fly only in green zones without prior permission, while yellow zones demand online clearance through Digital Sky. Red zones such as airports, military bases and government complexes are strictly prohibited. Altitude is capped at 120 m Above Ground Level (AGL) and Beyond Visual Line of Sight (BVLOS) spraying is allowed only in approved corridors with special authorisation.

Enforcement is strict, flying unregistered spray drones or using unapproved chemicals can lead to confiscation, fines up to ₹1 lakh, suspension of pilot licenses and prosecution under the Insecticides Act, 1968 and the Aircraft Act, 1934 (updated as Bharatiya Vayuyan Adhiniyam, 2024). These measures protect farmers, ensure environmental safety and build credibility for drone spraying in government schemes and insurance programs.

The importance of these requirements lies in balancing innovation with regulation. Drones can reduce labour costs, improve precision and minimize farmer exposure to chemicals but without strict rules, they could pose risks to air safety, public health and ecosystems. By following DGCA and CIB&RC guidelines, operators ensure that agricultural spraying is efficient, legal and sustainable.

Source: `Agricultural spraying requirements.docx` · Google Drive file id `1o-lrB45AObUqN-HBhpsW79j9PVtTwaIL` · folder “7. Drone regulations”

DGCA rules

Directorate General of Civil Aviation (DGCA) Rules

The Directorate General of Civil Aviation (DGCA) drone rules in India (updated through 2026) form the regulatory backbone for safe and legal drone operations. These rules are codified under the Drone Rules, 2021 (amended periodically) and they apply to manufacturers, operators and training organisations.

Registration & Certification

- Mandatory Registration: All drones above 250 g must be registered on the Digital Sky Platform and issued a Unique Identification Number (UIN).
- Remote Pilot Certificate (RPC): Required for drones above 2 kg or for commercial use. Training must be completed at DGCAapproved Remote Pilot Training Organisations (RPTOs).
- Type Certification: Manufacturers must obtain DGCA type certification before selling drones in India.

Operational Rules

- Altitude Limit: Maximum 120 m Above Ground Level (AGL).
- Airspace Classification:
- Green Zone: Free to fly up to 120 m without prior permission.
- Yellow Zone: Requires online permission via Digital Sky.
- Red Zone: Strictly prohibited (near airports, military bases, government sites).
- Visual Line of Sight (VLOS): Operators must maintain sight of the drone at all times.
- Night Flying: Prohibited unless specifically authorized.
- Flying Over People: Not permitted.
- Payload Restrictions: Carriage of dangerous goods or weapons is banned.

Safety & Compliance

- Remote ID: Mandatory for drones above 250 g, transmitting location and identification data.
- Insurance: Required for all commercial operations.
- Geofencing: Drones must comply with DGCAmandated geofencing to prevent entry into restricted zones.
- Emergency Protocols: Operators must follow DGCA guidelines for loss of communication or technical failure.

Penalties for Violations

- Unregistered Drones: Confiscation and fines.
- Flying in Restricted Zones: License suspension, drone seizure and criminal liability.
- Exceeding Altitude Limits: Monetary penalties and possible prosecution.
- Operating Without RPC: Suspension of operations and fines.

For farmers and entrepreneurs, DGCA rules are directly tied to subsidy schemes:

- Under Kisan Drone Yojana, only DGCAcertified drones and licensed pilots are eligible for subsidies.
- Under Namo Drone Didi, women SHGs receive drones bundled with DGCAapproved pilot training.
- Custom Hiring Centres (CHCs) and FPOs must employ certified operators to legally rent drones.

Source:

- Directorate General of Civil Aviation (DGCA): dgca.gov.in
- Digital Sky Platform: Official portal for drone registration and permissions.
- Ministry of Civil Aviation Notifications: Drone Rules, 2021 (with amendments up to 2026).
- Ministry of Agriculture & Farmers Welfare: Guidelines linking DGCA certification to Kisan Drone Yojana and Namo Drone Didi.

Source: `DGCA rules.docx` · Google Drive file id `1fUj0hEfXEoQ9eV_zKSblA4KU7M3-2IVP` · folder “7. Drone regulations”

Digital Sky

Digital Sky

The Digital Sky Platform is India's centralized online system developed by the Directorate General of Civil Aviation (DGCA) and the Ministry of Civil Aviation to regulate drones. It is the single gateway for everything related to unmanned aircraft systems registration, pilot licensing, flight permissions, compliance monitoring and enforcement. The platform was introduced to simplify drone governance, replacing fragmented approvals with a transparent, paperless and nationwide system.

To begin, every operator must create an account on Digital Sky by submitting identity proof (Aadhaar, PAN or passport), address proof and contact details. Once registered, the operator can add drones by entering manufacturer details, model, serial number and uploading the DGCA type certification. Only typecertified drones are accepted, ensuring safety and standardization. After paying a nominal fee, the system issues a Unique Identification Number (UIN), which functions like a license plate and must be physically affixed to the drone. This UIN is digitally linked to the operator's profile and, if applicable, their Remote Pilot Certificate (RPC).

Digital Sky also manages flight permissions. The platform displays an interactive airspace map divided into green, yellow and red zones. In green zones, drones can fly up to 120 meters Above Ground Level without prior approval. In yellow zones, operators must request permission online, which is usually granted within minutes. Red zones such as airports, military bases and government sites are strictly prohibited. Every flight is logged digitally and drones must have Remote ID enabled to transmit their location and operator details. Geofencing technology ensures drones cannot enter restricted zones.

For pilots, Digital Sky integrates with DGCAapproved Remote Pilot Training Organisations (RPTOs). Training certificates are uploaded directly, linking the pilot's credentials to their registered drones. Insurance policies for commercial drones are also uploaded, ensuring coverage before operations begin. Ownership changes such as sale, transfer or decommissioning must be updated on the platform, keeping the registry current.

Enforcement is strict: flying unregistered drones above 250 g can lead to confiscation and fines up to ₹1 lakh. Operating without a UIN or RPC can result in license suspension. Tampering with Remote ID or flying in restricted zones carries criminal liability under the Aircraft Act, 1934.

The importance of Digital Sky lies in its ability to provide legal protection, accountability and safety. It ensures that every drone is traceable to its owner, integrates drones into India's aviation ecosystem and balances innovation with regulation. For operators, following Digital Sky guidelines is not optional it is the only way to fly legally in India.

Source: `Digital Sky.docx` · Google Drive file id `1V4BuWRE7ZQQj8_Gb9ph_HpJWNpPP6TID` · folder "7. Drone regulations"

Drone categories

Drone Categories

Nano Drones

Nano drones are the smallest category, weighing up to 250 grams. They are exempt from registration and licensing requirements, making them accessible for hobbyists and educational use. They can be flown indoors or in enclosed areas and outdoors only up to 15 meters Above Ground Level (AGL) in green zones. Because of their lightweight nature, they pose minimal risk to aviation safety. Nano drones are commonly used for basic photography, recreational flying and STEM education projects. They are not eligible for agricultural subsidies but they serve as training tools for beginners.

Micro Drones

Micro drones weigh between 250 grams and 2 kilograms. They require registration with DGCA and issuance of a Unique Identification Number (UIN). For recreational use, no license is needed but for commercial operations such as mapping, surveillance or agricultural scouting a Remote Pilot Certificate (RPC) is mandatory. Micro drones can fly up to 60 meters AGL in green zones. They are often used by startups for surveying, smallscale

crop monitoring and security patrols. In agriculture, they are suitable for scouting pest infestations or monitoring crop health but are not powerful enough for spraying.

Small Drones

Small drones weigh between 2 kilograms and 25 kilograms. This is the most important category for agriculture. Registration and a UIN are mandatory and operators must hold a Remote Pilot Certificate issued by DGCA after training at an approved RPTO. These drones can fly up to 120 meters AGL in green zones, with permissions required in yellow zones. Small drones are eligible for subsidies under the Kisan Drone Yojana (40–75% subsidy depending on farmer category) and Namo Drone Didi Scheme (80% subsidy for women SHGs). They are used for pesticide spraying, nanourea application, fertilizer distribution and soil testing. A single drone can spray 1 acre in 7–10 minutes, saving 25–40% pesticide and reducing water use tenfold. Custom Hiring Centres (CHCs) and Farmer Producer Organisations (FPOs) typically purchase small drones and rent them to farmers at ₹5,000–10,000 per day, creating rural entrepreneurship opportunities.

Medium Drones

Medium drones weigh between 25 kilograms and 150 kilograms. They require strict DGCA licensing, insurance and special authorization for each operation. These drones are not commonly used in agriculture due to their size and cost but are deployed in industrial inspections, infrastructure monitoring and heavy payload delivery. They can fly higher than small drones but only with DGCA clearance. Medium drones are relevant for logistics companies and largescale industrial projects rather than smallholder farming.

Large Drones

Large drones weigh more than 150 kilograms. They are treated like aircraft under DGCA rules and require full aviation certification, including Air Traffic Control (ATC) clearance for every flight. These drones are used in defense, cargo transport and specialized industrial applications. They are not part of agricultural subsidy schemes and are operated only by government agencies or licensed corporations.

Compliance & Safety Across Categories

- Digital Sky Platform: All drones above 250 g must be registered here.
- Remote ID: Mandatory for drones above 250 g, transmitting identification and location data.
- Geofencing: Prevents drones from entering restricted zones.
- Insurance: Required for all commercial drones.
- Penalties: Flying unregistered drones, exceeding altitude limits or operating without a Remote Pilot Certificate can lead to confiscation, fines and criminal liability.

Source:

- Directorate General of Civil Aviation (DGCA): Drone Rules, 2021 (amended 2022–2026) – dgca.gov.in
- Digital Sky Platform: digitalsky.dgca.gov.in
- Ministry of Civil Aviation Notifications (2023–2026)
- Ministry of Agriculture & Farmers Welfare: agrimachinery.nic.in

Source: `Drone categories.docx` · Google Drive file id `1sgRLyfw1mSP6E9r8GE1MzL426vP-etyi` · folder “7. Drone regulations”

Drone registration

Drone Registration

Eligibility for Registration

Drone registration is compulsory for all drones above 250 grams.

- Nano drones (≤250 g) used recreationally are exempt.
- Micro drones (250 g – 2 kg) must be registered if used commercially.
- Small drones (2 – 25 kg) require registration in all cases.
- Medium and Large drones are treated like aircraft and need full DGCA clearance.

This classification ensures that hobbyists with very light drones are not burdened, while commercial operators are strictly regulated.

Step 1: Create Account on Digital Sky

The Digital Sky Platform (digitalsky.dgca.gov.in) is the official portal.

- You create a pilot/operator profile.
- Provide identity proof (Aadhaar, PAN, or passport).
- Provide address proof (utility bill, rental agreement, or government ID).
- Link your mobile number and email for OTP verification.

This account becomes your permanent aviation profile.

Step 2: Submit Drone Details

You must enter:

- Manufacturer name and model.
- Serial number and specifications.
- Type certification details (DGCA only registers typecertified drones).
- Purpose of use (commercial, agriculture, survey, etc.).

If the drone is imported, customs clearance and type certification must be uploaded.

Step 3: Upload Documents

- Proof of identity and address.
- Remote Pilot Certificate (if already obtained).
- Insurance policy (mandatory for commercial drones).
- Manufacturer’s type certificate.

DGCA crosschecks these with its database before approval.

Step 4: Pay Registration Fee

- Nominal fee: ₹100–₹1,000 depending on category.
- Payment is online via Digital Sky.
- Receipt is generated and linked to your drone profile.

Step 5: Issuance of UIN (Unique Identification Number)

- Each drone receives a UIN, like a license plate.
- Must be physically affixed to the drone.
- Linked digitally to the operator’s profile and Remote Pilot Certificate.
- Enables Remote ID transmission during flight, so authorities can track drone location and operator details.

Step 6: Operational Compliance

Once registered, you must follow DGCA rules:

- Fly only in green zones without prior permission.
- Request permission via Digital Sky for yellow zones.
- Never fly in red zones (airports, military bases, government sites).
- Maximum altitude: 120 m Above Ground Level (AGL).
- Flights must remain within Visual Line of Sight (VLOS).
- Night flying is prohibited unless DGCA grants clearance.

Step 7: Renewal & Updates

- Registration is valid for the drone's operational life.
- Ownership changes (sale, transfer, or decommissioning) must be updated on Digital Sky.
- Annual compliance checks may be required for commercial drones.

Source:

- DGCA Drone Rules, 2021 (amended 2022–2026) – dgca.gov.in
- Digital Sky Platform – digitalsky.dgca.gov.in
- Ministry of Civil Aviation Notifications (2023–2026)
- Press Information Bureau (PIB Delhi releases, 2023–2026)

Source: `Drone registration.docx` · Google Drive file id `1eljL8ZJVMn9nKhuPSTxPieweSNXiUEz0` · folder "7. Drone regulations"

Insurance

Insurance

Types of Coverage and Amounts

- ThirdParty Liability: This is the backbone of drone insurance. It covers injury to people or damage to property caused by drone operations. For example, if a spraying drone crashes into a farmhouse or injures a worker in the field, liability insurance pays compensation. Coverage typically ranges from ₹5 lakh to ₹50 lakh, depending on drone category and risk profile.
- Hull Insurance: Protects the drone itself against physical damage crashes, theft, fire or water ingress. Agricultural drones are expensive (₹5–15 lakh for medium payload models), so hull insurance is critical. Coverage usually ₹1 lakh to ₹25 lakh, based on drone market value.
- Payload Liability: Covers damage caused by payload malfunction. For spraying drones, this means pesticide drift, nozzle failure or accidental overapplication. Coverage generally ₹2 lakh to ₹10 lakh for agricultural spraying drones.
- Environmental Liability: Protects against chemical drift, contamination of water sources or damage to neighboring crops. This is especially important in villages where fields are closely packed. Coverage usually ₹2 lakh to ₹10 lakh, depending on crop type and chemical risk.
- BVLOS Endorsement: Extra coverage for Beyond Visual Line of Sight operations in approved corridors. Since BVLOS flights carry higher risks, insurers add special endorsements. Adds ₹10 lakh to ₹20 lakh on top of standard liability.

Premiums and Claim Process

- Premiums: Typically 2–5% of insured value annually.
- Example: For a ₹10 lakh spraying drone, premium is ₹20,000–₹50,000 per year.
- Claims: Require incident report, flight logs, proof of compliance with DGCA and CIB&RC rules. If a drone crashes during spraying, the operator must submit logs showing altitude, weather conditions and chemical used.
- Deductibles: Usually 5–10% of claim amount. For a ₹5 lakh claim, operator may pay ₹25,000–₹50,000 out of pocket.

Enforcement

Flying uninsured drones can lead to:

- Confiscation of drone by authorities.
- Fines up to ₹1 lakh.
- Suspension of Remote Pilot Certificate (RPC).
- Denial of UIN renewal.

Insurance is also mandatory for participation in government subsidy schemes and farmer service contracts. Without valid insurance, drone operators cannot legally provide spraying services to farmer groups or cooperatives.

Source:

- DGCA Drone Rules, 2021 (amended 2022–2026) – dgca.gov.in
- IRDAI UAV Insurance Guidelines (2025–2026) – irdai.gov.in

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No-flyrestricted zones

No fly/restricted zones

In India, NoFly Zones for drones are strictly defined by the Directorate General of Civil Aviation (DGCA) under the Drone Rules, 2021 (amended through 2026) and enforced through the Digital Sky Platform. These zones are areas where drone operations are completely prohibited due to safety, security or privacy concerns. They are digitally mapped into the airspace system as red zones and drones equipped with geofencing technology are automatically prevented from entering them. NoFly Zones include airports and airfields, where drones could interfere with aircraft takeoff and landing, military installations, such as bases, camps and training grounds, where drones could pose espionage or security threats, international borders, where unauthorized flights could compromise national security, government buildings like Parliament, Secretariat and Raj Bhavan, nuclear power plants and research facilities, where drones could endanger critical infrastructure, and prisons or police headquarters, where surveillance or contraband delivery risks exist.

To ensure compliance, operators must check the interactive airspace map on the Digital Sky Platform before flying. The map divides airspace into green zones (where drones can fly up to 120 m Above Ground Level without prior approval), yellow zones (where online permission is required) and red zones (strictly prohibited). Enforcement is carried out through Remote ID tracking, which transmits drone location and operator details in real time and geofencing, which prevents drones from entering restricted areas. Violations carry heavy penalties: confiscation of the drone, fines up to ₹1 lakh, suspension of pilot licenses and even criminal prosecution under the Aircraft Act, 1934 (replaced by the Bharatiya Vayuyan Adhiniyam, 2024).

The importance of NoFly Zones lies in their role in maintaining air safety, national security and public protection. They prevent collisions with aircraft, safeguard sensitive installations and ensure that drones are not misused near crowds or government sites. For operators, adhering to these guidelines is not optional, it is the only way to fly legally in India.

Source of information:

- DGCA Drone Rules, 2021 (amended 2022–2026) – dgca.gov.in
- Digital Sky Platform – digitalsky.dgca.gov.in
- Ministry of Civil Aviation Notifications (2023–2026)
- Press Information Bureau (PIB Delhi releases, 2023–2026)

Source: `No-flyrestricted zones.docx` · Google Drive file id `1NUkohr9J6o9hMxBO_z8MKo1jsfHBJlok` · folder "7. Drone regulations"

Pilot requirements

Pilot Requirements

To legally operate drones in India in 2026, pilots must meet DGCA's strict requirements: be at least 18 years old, have passed Class 10, complete training at a DGCAapproved Remote Pilot Training Organisation (RPTO), and obtain a Remote Pilot Certificate (RPC). This license is mandatory for all commercial operations and for drones above 2 kg.

Eligibility Requirements

- Age: Minimum 18 years.
- Education: At least Class 10 pass (matriculation).
- Medical Fitness: Basic medical certificate confirming fitness to operate.
- Background: No disqualifying criminal record under aviation law.

Training Process

- Conducted at DGCAapproved RPTOs across India.
- Duration: Typically 10–15 days.
- Curriculum includes:
- Drone assembly and maintenance.
- Airspace rules and classifications (green, yellow, red zones).
- Emergency procedures and incident reporting.
- Practical flight training with mandatory logged hours.
- Assessment: Written exam + flight test.

Certification

- Remote Pilot Certificate (RPC): Issued after successful training and assessment.
- Validity: 10 years, renewable.
- Required for Micro drones (commercial use) and all Small, Medium, and Large drones.
- RPC is uploaded to the Digital Sky Platform, linked to the pilot's registered drones.

Operational Rules for Licensed Pilots

- Must operate within Visual Line of Sight (VLOS).
- Maximum altitude: 120 m Above Ground Level (AGL).
- Must request permission via Digital Sky Platform for flights in yellow zones.
- Red zones (near airports, military bases, government sites) are strictly prohibited.
- Night flying is banned unless DGCA grants special clearance.
- Remote ID must be active on all drones above 250 g.

Enforcement & Penalties

- Flying without RPC: Fines up to ₹1 lakh and possible imprisonment under the Aircraft Act, 1934.
- Unregistered drones (>250 g): Confiscation and penalties.
- Exceeding altitude limits: License suspension and fines.
- Flying in restricted zones: Criminal liability and drone seizure.
- Legal protection: Ensures compliance with aviation law.
- Commercial viability: Clients demand proof of licensing before hiring operators.
- Insurance coverage: Drone insurance policies require a valid RPC.
- Airspace access: Licensed pilots can request permissions for controlled zones.

Source:

- Directorate General of Civil Aviation (DGCA) – Drone Rules, 2021 (amended 2022–2026).
- Digital Sky Platform (digitalsky.dgca.gov.in) – registration, licensing, permissions.

Source: `Pilot requirements.docx` · Google Drive file id `1m5x7mlm4LA7cXWzC-EoBhuMc_ZU44z-Y` · folder “7. Drone regulations”

Remote pilot certification

Remote pilot certification

Step 1: Eligibility Check

- Age Requirement → Minimum 18 years.
- Education Requirement → Must have passed Class 10.
- Medical Fitness → Basic medical certificate confirming fitness.

Step 2: Enroll in Training

- Register at a DGCAapproved Remote Pilot Training Organisation (RPTO).
- Duration: 10–15 days.
- Curriculum includes:
- Drone assembly & maintenance.
- Airspace rules (green, yellow and red zones).
- Aviation meteorology & aerodynamics.
- Emergency procedures & incident reporting.
- Practical flight training with logged hours.

Step 3: Assessment

- Written Exam → Covers theory (air regulations, safety, meteorology).
- Flight Test → Demonstrates practical flying skills.
- Evaluation → Conducted by RPTO instructors under DGCA guidelines.

Step 4: Certification

- Successful candidates are issued a Remote Pilot Certificate (RPC).
- Validity: 10 years, renewable.
- RPC is uploaded to the Digital Sky Platform, linked to pilot and drone UIN.

Step 5: Operational Rules

- Fly only within Visual Line of Sight (VLOS).
- Maximum altitude: 120 m Above Ground Level (AGL).
- Permission required for yellow zones via Digital Sky.
- Red zones strictly prohibited.
- Night flying banned unless DGCA grants clearance.
- Remote ID must be active on drones above 250 g.

Step 6: Compliance & Enforcement

- Flying without RPC: Fines up to ₹1 lakh + imprisonment under Aircraft Act, 1934.
- Unregistered drones (>250 g): Confiscation and penalties.
- Exceeding altitude limits: License suspension and fines.
- Flying in restricted zones: Criminal liability and drone seizure.

Eligibility → Training at RPTO → Written Exam + Flight Test → RPC Issued → Upload to Digital Sky → Operate within Rules → Compliance & Renewal

- Directorate General of Civil Aviation (DGCA): Drone Rules, 2021 (amended 2022–2026) – dgca.gov.in

Source: `Remote pilot certification.docx` · Google Drive file id `10sG_Z9zPZ6Y7WCeNztwGHPHu2FDL3qif` · folder "7. Drone regulations"

8. Agricultural University Research

ICAR, state agricultural university, KVK and government research on drone spraying, spray technology, crop protection, spray volume, drone efficiency, field trials and pest/disease management

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Design and Development of a Drone for Spraying Pesticides, Fertilizers and Disinfectants Karan Kumar Shaw1, Vimalkumar R. 2 1,2

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Abstract - There are too many technologies involved in today’s Agriculture, out of which spraying pesticides using drones is one of the emerging technologies. Manual pesticide spraying causes many harmful side effects to the personnel involved in the spraying process. The Exposure effects can range from mild skin irritation to birth defects, tumors, genetic changes, blood and nerve disorders, endocrine disruption, coma or death. The WHO (World Health Organization) estimated as one million cases of ill affected, when spraying the pesticides in the crop field manually. This paved the way to design a drone mounted with spraying mechanism having 12 V pump, 6 Litre storage capacity tank,4 nozzles to atomize in fine spray , an octocopter configuration frame ,suitable landing frame, 8 Brushless Direct Current (BLDC) motors with suitable propellers to produce required thrust about 38.2 KG(at 100% RPM) and suitable LithiumPolymer (LI-PO) battery of current capacity 22000 mAh and 22.2 V to meet necessary current and voltage requirements. A First-Person View (FPV) camera and transmitter can also be fixed in the drone for monitoring the spraying process and also for checking pest attacks on plants. This pesticide spraying drone reduces the time, number of labor and cost of pesticide application. This type of drone can also be used to spray disinfectant liquids over buildings, water bodies and in highly populated areas by changing the flow discharge of the pump. Key Words: DRONE, AGRICULTURE, PAYLOAD, SENSORS, PUMP, SPRAY

- INTRODUCTION The Indian Agricultural sector is the most important sector as it amounts to a staggering 18% of India’s Gross Domestic Product (GDP) and also provides employment to 50% of the national human workforce. Our country is dependent on agriculture so much, has yet to tap into the real potential of agriculture, because of improper methods of monitoring crops and the irrigation patterns and the pesticides required to be applied. In India, there are over 35 drone start-ups that are working to raise the technological standards and reduce the prices of agricultural drones. This project aims to develop Unmanned Aerial Vehicle (UAV) for overcoming this problem and also spay large amounts of pesticides within smaller interval of time using Octocopter. 1.1 Literature Survey Dongyan et al. (2015) [1] experimented on effective swath width and uniformity of droplet distribution over aerial spraying systems like M-18B and Thrush 510G.These agricultural planes flew at height of 5 m and 4 m respectively and with this experiment they reach to conclusion that flight height leads to the difference in swath width for M-18B & Thrush 510G.

Huang et al. (2015) [2] made a low volume sprayer which is integrated into unmanned helicopters. The helicopter has a main rotor diameter of 3 m and a maximum payload of 22.7 kg. It used to require at least one gallon of gas for every 45 minutes. This study paved the way in developing UAV aerial application systems for crop production with higher target rate and larger VMD droplet size. Yallappa et al. (2017) [3] developed an hexacopter with 6 BLDC motors and two LiPo batteries of 6 cells- 8000 mAh. Their study also involves performance evaluation on discharge and pressure of spray liquid, spray liquid loss and determination of droplet size and density. Through their project, they finally made a drone capable of carrying 5.5 L of liquid with an endurance time of 16 min. Kurkute et al. (2018) [4] worked on quadcopter UAV and its spraying mechanism using simple cost-effective equipment. The universal sprayer system is used to spray for both liquid and solid content. In their research, they have also compared different controllers needed for agricultural purposes and concluded that quadcopter system with Atmega644PA is the most suitable due to its efficient implementation. Rahul Desale et al. (2019) [5] described an architecture based on UAV that could be employed for agricultural applications. Their UAV was designed not only for spraying but also for monitoring agricultural fields with the use of cameras and GPS. Their design was optimized for cost and weight. They used a microcontroller kk 2.1.5 which has inbuilt firmware. Prof. B. Balaji et al. (2018) [6] developed an hexacopter UAV with the purpose of spraying pesticides as well as crop and environment monitoring using Raspberry Pi that run on python language. Their UAV also contains multiple sensors like DH11, LDR, Water Level Monitoring sensors. From this experiment, they finally concluded that with proper implementation of UAVs in the agricultural field almost 20%90% savings in terms of water, chemical maltreatments and labor can be expected. 2. DESIGN AND WORKING OF OCTOCOPTER To Design an octocopter first we have to Estimate our payload, then with respect the weight of the payload motor, Propeller, Electronic Speed Controller, Pump, First Person View camera and video transmitter has to be selected. Battery has to be selected by knowing the current and voltage requirements of the components. Then the thrust requirement has to be calculated and finally the frame of the copter has to be designed by determining required arm number, arm length and application of payload.

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2.1 Payload Estimation The weight of the payload is calculated by taking the weight of the liquid (pesticide or disinfectant), storage tank of 6 Litre capacity, pump and nozzles. Table -1: Payload Data PARTS

WEIGHT (grams)

6 Litre liquid

6000

6 Litre liquid tank

250

pump

200

Nozzle Total

300 6750

2.2 Construction The prefix octo-copter implies (“octo” =eight), is a drone configuration where there are eight arms. The main frame is made of carbon fiber composite material with each arm length of 492 mm. At each free end of the arm, a motor will be fixed and propeller will be mechanically coupled to the motor. For all eight motors the output side of an ESC will be connected and the input side of the Electronic Speed Controller (ESC) will be connected to the flight controller. The other input of the ESC will be connected to the power distribution board where the power supply is provided by the Li-Po battery. In a similar fashion all the other ESC’s, motors and propellers are connected. A receiver will be connected to the Flight controller to receive signals from the

transmitter. An FPV camera and a suitable transmitter connected each other is connected to the flight controller. The storage tank of dimensions 200 x 300 x 110 mm is mechanically coupled to the frame, the bottom of the tank will have a slope so that the entire tank gets drained completely. A plastic tube of 1.3 meters length and four nozzles are fixed at 45cm between each other. A pump is powered from a power distribution board, the inlet of the pump is connected to the storage tank and the outlet is connected to the plastic tube where nozzles are fixed. The landing frame of height 300mm is connected to the main frame so that the landing of the drone will be safe and the storage tank will not touch the ground. 2.3 Working The signals will be transmitted from Transmitter and it will be received by the Receiver in the drone. From the receiver the signal goes to the Flight controller where the signal will be processed with accelerometer and gyroscope sensors. The processed signal will be sent to the ESC, which allows the specific amount of current to the motor based on the signal it receives. The propellers are mechanically coupled to the motors so that they rotate and produce thrust. The FPV camera takes current supply from the flight controller and it records the video, the video signals will be processed by the transmitter and it will be received by the receiver in ground. The pump takes current supply from the Li-Po battery and pressurizes the liquid from the storage tank then the pressurized liquid flows through the pipeline and enters the nozzle then gets sprayed. The flow rate of the pump can be controlled by varying the input current which can be controlled from the transmitter.

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Fig -1: Block diagram of working process

2.4 Components Used 2.4.1 Motor Outer runner BLDC motors in which there are no brushes, they have a permanent magnet. The RPM of the motor can be controlled by varying the input current. This motor TMOTOR MN 7005 KV115 and P24x7.2F propeller produces a maximum thrust of 4783 grams.

Fig -2: T-MOTOR MN 7005 KV115

2.4.2 Propeller The propeller is of 24 inches length and has 7.2 inches pitch. It is made up of carbon fiber which possesses high strength to weight ratio when compared to the propellers made up of plastics.

Fig -3: T-MOTOR Propeller P24X7.2CF

2.4.3 ESC It stands for Electronic Speed Controller and it is used to vary the Revolution Per Minute (RPM) of the motor. 60A rated ESC is used as per the motor and battery specifications.

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Fig -4: Flame 60A HV

2.4.4 Battery The battery that can be used is a Li-Po battery of 22000mAh capacity and 22.2 V. In this battery six Li-Po cells are connected in series (6x3.7=22.2V).

Fig -7: Fly sky CT6B 2.4 6CH Transmitter and FS-R6B Receiver

2.4.7 FPV Camera and Transmitter The camera that can be used is HD FPV camera 1200 TVL, it has 2.8mm Lens, auto/color/ black & white Day and night format.TS5828 32CH mini transmitter can be connected to the camera for transmission of video signals to receiver at ground.

Fig -5: Li-Po battery

2.4.5 Flight Controller The flight controller helps in the maneuvering operations and also it provides Auto level function. The accelerometer and gyroscope sensors in the Flight controller processes the signals from the receiver and gives the output to the ESC. The KK 2.1.5 Flight controller board can be used in the drone as it has inbuilt firmware. The features of this Flight controller board are much easier for calibration. It uses ATMEL Mega 644PA 8-bit AVR RISC-based microcontroller with 64K of memory.

Fig -8: FPV camera

Fig -9: Video Transmitter

5.8G UVC receiver is used to receive the video signals. It can be connected to the android mobile which has installed the GO FPV application in it. Fig -6: KK 2.1.5 Multi-Rotor LCD Flight controller

2.4.6 Radio Transmitter and Receiver The Transmitter and receiver used are FlySky CT6B 2.4Ghz 6CH and FS-R6B respectively. This combination provides a range of about 1000 meters. This Transmitter and receiver provide upto 6 channel options.

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Fig -10: 5.8 UVC OTG Receiver

2.4.8 Pump and Nozzle To pressurize the liquid a 12 V DC water pump can be used which has 2.5 L/min capacity can be used. Then the pressurized liquid enters the nozzle and gets sprayed. The nozzle that can be used is a flat fan type for spraying the liquid. Four nozzles are connected with ducts and they are palace at 45cm distance between each other.

The overall weight of the drone is calculated by adding the total weight of components and the weight of payload. Overall weight = Payload + Weight of components = 6750 + 5946 = 12,696 grams(approx.) 2.6 Thrust Calculation Thrust developed at 100% RPM can be three times larger than the total weight of the drone so that the drone has better maneuverability and the drone can climb higher altitudes with higher rate of climb. Thrust produced by one propeller with one motor= 4783 grams Total thrust produced = 8 x 4783 = 38264 grams Thrust to weight Ratio = Thrust produced / total weight of drone = 38264 / 12696 = 3.01 : 1 2.7 Battery Drain Time Calculation The Battery Drain time can be more than 10 minutes so that the drone drains the entire storage tank and it can be refilled for another serve. For a safer side, the battery drain time has to be calculated by considering the distance and time for the drone to return safely. Table -3: Current Requirement Table

Fig -11: Pump

Fig -12: Flat fan Nozzle

2.5 Weight Build-up Table -2: Components Weight Datasheet PARTS Frame Battery Motor (8) ESC (8) + power distributor Propeller (8) Flight controller TOTAL

COMPONENT

CURRENT REQUIRED (Amp)

Motor Receiver

120 0.1

Flight controller

0.1

ESC (8) Camera FPV transmitter pump TOTAL

0.8 0.32 0.31 5 126.63

Current output from battery= 22000 MAh Total current consumption of all components = 126.63 A Battery endurance = current output from battery/ Total current consumption of all components = 22000 MAh / 126.63A = 22*60 / 126.63 A = 10.42 MINS. (AT 100% THROTTLE) 2.8 Structural Description There is no such generic frame which is considered to be best among all the frames, however it depends on a number of factors like multi-rotor configuration, rotating moment and balancing, application, material, stiffness and components integration. Depending on size and dimensions of selected electronic components, we designed a base plate in the shape of irregular octagon such that all components placed on the Centre of Gravity. The dimensions in mm are briefly mention on figure 13.

WEIGHT (grams) 2000 (Approx.) 1386 1504 588 448 20 5946

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The tank being placed at the CG of the drone having capacity of 6 Litre having slanting bottom to prevent liquid stagnation during gravity feed. It is made up of Polyethylene which is the most common plastic tank material as it is relatively immune to damage to salt water. Any non-hazardous liquid can be used in the tanks for the purpose spraying.

Fig -13: 2D Drawing

We decided to use shorter four “Y-shaped” arms rather than going for longer 8 straight arms as it could reduce weight. Moreover, the former configuration has more stable thrust balancing and smaller in size which make it easier to carry as compared to the latter. The dimensioning of arms was done maintaining the minimum gap of 5 cm between propellers and angles between two arms of Y is subjective to application of drone. The cross-section of the arms were hollow circular rods because it can withstand the same stress as that of solid rods. In torsion the stress profile is a linear relationship with diameter. Strength to weight ratio is better for a hollow pipe than a solid rod. This means a hollow cylinder is stronger than a rod of equal mass and the same material. The selection of material is as crucial as selection of configuration of arms. The material plays a significant role in determining the drone’s stability and efficient performance. The material for the arms was chosen as carbon fibre due to its properties like light weight and higher strength- to-weight ratio. However, the radio and antenna were connected properly to stop the radio signal interference by carbon fibers. The material for base plate was selected as Carbon/Kevlar composite due to its properties like high tensile strength, no shrinkage and embrittlement at extreme temperature, scratch and electrically resistant. The landing frame is made up of aluminium alloy owing to its light weight and yield strength. The cad model of our design as shown in figure 13 is made in SOLIDWORKS 20.

Fig -14: CAD Model of Drone

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- CONCLUSIONS In this paper we have described a design of a drone mounted spraying mechanism for Agricultural purpose and for spraying disinfectants. This method of spraying pesticides on Agricultural fields reduces the number of labours, time, cost and the risk involved to the personnel involved in spraying the liquids. This drone can also be used in spraying disinfectant liquids over buildings, water bodies and highly populated areas. 4. FUTURE SCOPE ➢ Under the current COVID19 Pandemic situation, it can be used to sanitize large hotspots areas without actually going there in person. ➢ Manual control can be changed into autonomous control with GPS technology and auto return home option. ➢ With image processing techniques, the drone can be involved in surveillance to determine the pest attack on the plants, condition of ripening fruit. REFERENCES [1]

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Embracing drones and the Internet of drones systems in manufacturing – An exploration of obstacles Dauren Askerbekov a , Jose Arturo Garza-Reyes b, c, * , Ranjit Roy Ghatak d , Rohit Joshi e , Jayakrishna Kandasamy f , Daniel Luiz de Mattos Nascimento g a

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A R T I C L E I N F O

A B S T R A C T

Keywords: Drone Internet of drones IoD Unmanned aerial vehicle UAV Manufacturing Industry Barriers AHP EFA

The manufacturing sector attributes the growing prominence of Drones and the Internet of Drones (IoD) systems to their multifaceted utility in delivery, process monitoring, infrastructure inspection, inventory management, predictive maintenance, and safety inspections. Despite their potential benefits, adopting these technologies faces significant obstacles that need systematic identification and resolution. The current literature inadequately addresses the barriers impeding the adoption of Drones and IoD systems in manufacturing, indicating a research gap. This study bridges this gap by providing comprehensive insights and facilitating the organisational transition towards embracing Drone and IoD technologies. This research identifies 20 critical barriers to deploying Drones and IoD in manufacturing. These barriers are validated through a global quantitative survey of 120 Drone experts and analyzed via Exploratory Factor Analysis (EFA). EFA categorises these challenges into six distinct dimensions. Utilizing the Analytical Hierarchy Process (AHP), these dimensions and individual barriers are ranked, incorporating feedback from five Drone specialists. The study highlights 'Safety and Human Resource Barriers' and 'Payload Capacity and Battery Barriers' as the most predominant obstacles. Key concerns include limited battery life, explosion risks, and potential damage to assets and individuals. This research significantly advances the existing literature by presenting a practical methodology for categorising and prioritising Drone and IoD adoption barriers. Employing EFA and AHP offers a globally relevant framework for stakeholders to strategically address these challenges, advancing the integration of drones and IoD systems in the manufacturing domain.

- Introduction The manufacturing landscape is transforming with the integration of advanced technologies, signalling the progression from traditional practices to Industry 4.0 and beyond [1,2]. Technologies like IoT, advanced analytics, RFID, automated storage systems, and robotics address specific challenges, improving

supply chain management, inventory optimization, and workers' safety [3]. Among these technologies, Unmanned Aerial Vehicles (UAVs), commonly known as drones, and their networked systems under the framework of the Internet of

Drones (IoD) stand out as particularly revolutionary [4]. Various sectors, including manufacturing, are increasingly repurposing drones for commercial use to enhance operational efficiency, worker safety, and inventory management [4,5]. Initially developed for military use, drones have significantly broadened their applications, demonstrating substantial impact across various sectors [6]. In agriculture, drones have revolutionized precision farming, enhancing crop yields by up to 30 % and reducing water and chemical use by approximately 50 %, optimizing resource management [7,8]. The logistics industry has also seen transformative changes, with

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RQ1 What are the primary barriers to adopting drones and the Internet of drone systems in the manufacturing industry? RQ2 What is the relative significance of each barrier that hinders the adoption of drones and the Internet of Drone systems in manufacturing operations? RQ3 What implications do barriers to adopting drones and the Internet of Drone systems pose for advancing technology adoption in the manufacturing industry?

companies like Amazon reducing delivery times and costs by up to 50 % through drone integration [9,10]. Drones contribute significantly to environmental conservation and disaster management by enabling efficient real-time data collection in affected areas [11,12]. The commercial drone market has experienced robust growth, valued at approximately $19.89 billion in 2022, with projections of a 13.9 % compound annual growth rate through 2030 ([13]Share & Trends Report 2030, n.d.). Expanded applications in sectors like construction drive this growth, as drones reduce surveying times by 85 %, enhancing project efficiency and safety [14]. Technological advancements and adaptive regulatory frameworks globally, such as those by the Federal Aviation Administration (FAA), have supported this surge, with over 500,000 drones registered for commercial use in the USA by 2021 [15]. In rural areas, drones are crucial for delivering essential medical supplies in regions like sub-Saharan Africa, showcasing their effectiveness locally and nationally ([16] | UNICEF Supply Division, n.d.). Urban centres in Europe also benefit, with drone delivery services projected to be economically viable for about 30 % of the population, expected to reduce delivery times, operational costs, and CO2 emissions [17]. Additionally, legislative adaptations in countries like Norway facilitate the integration of drones into their transportation systems, illustrating a proactive approach to embracing autonomous vehicle technologies [18]. This global adoption underscores the diverse capabilities of drones, marking them as integral to the future of industrial and service sectors worldwide. Recent research comprehensively examines the complex barriers to adopting Drones and the Internet of Drones (IoD) systems across various sectors, including agriculture, construction, healthcare, transportation, and logistics, underscoring significant technological, operational, regulatory, and societal challenges [8,19–21]. The literature highlights the importance of integrating both technological innovations and socio-economic strategies to facilitate the adoption of drone technologies in industrial environments. This integration is crucial for aligning with broader efficiency and productivity goals while adapting to specific operational and market conditions [19,21,22]. Strategic frameworks are necessary to address the vast array of barriers to drone adoption, calling for robust policies that support the scalability of these technologies across diverse industrial landscapes [23]. Region-specific studies from India and Europe provide insights into local regulatory and socio-economic factors influencing drone integration, enriching our understanding of the implementation of advanced manufacturing technologies [8,23]. These investigations highlight the global nature of the shift towards innovative manufacturing technologies and illustrate the need for an integrated, multifaceted approach in adopting

drones and IoD systems for manufacturing processes. The surge in drone usage for industrial applications marks a transformative approach to enhancing operational efficiency and reducing the environmental footprint of manufacturing systems [24]. While existing research primarily focuses on generic barriers to drone adoption, such as regulatory obstacles [25] and technological challenges [26], it often neglects specific challenges in the manufacturing sector's integration of advanced aerial technologies. Although studies like Zhong et al. [27] and Kas and Johnson [28] address issues like drone path planning and safety hazards, comprehensive exploration of systemic and regulatory hurdles is lacking. Additionally, while valuable insights are offered within European industrial contexts [29] and perspectives from the European Steel Industry [30], the broader complexities of transitioning to drone-integrated manufacturing paradigms remain underexplored. Addressing this research gap, our research endeavours to meticulously discern, authenticate, and prioritize impediments confronting global EV deployment for LMD. Within the context of the current study, the research aims to address the following research questions.

This study enhances the discourse on drone adoption within the manufacturing sector by addressing critical research questions that explore the multifaceted barriers impeding the integration of drones and Internet of Drones (IoD) systems into advanced industrial operations. Unlike previous research that predominantly focuses on technological aspects [31], our investigation delves into the socio-technical, financial, and operational challenges, providing a granular analysis of the systemic and regulatory hurdles that affect drone deployment in manufacturing environments. This research is grounded in a global perspective, gathering insights from various regions to understand the universal barriers and opportunities for drone integration in manufacturing, leading to actionable strategies developed through extensive stakeholder consultations. Our comprehensive framework integrates technological, operational, socio-technical, and policy-related challenges, offering a cohesive understanding of these impediments and their implications for advanced manufacturing systems. By contrasting our holistic approach with segmented analyses found in existing literature, such as the efficiency assessments by Zhong et al. [27] and safety evaluations by Kas and Johnson [28], this study highlights its innovative contributions to the field. It calls for further research and policy development to facilitate a transition towards more integrated and sustainable manufacturing operations, thus addressing a critical gap in existing scholarly work. The paper is structured as follows: Section 2 offers a literature review focusing on Drones and IoD benefits for manufacturing and its implementation challenges. Section 3 describes the adopted research methodology. Section 4 presents the findings from the barriers analysis. Section 5 delves into an in-depth discussion of the results, while the paper culminates in the conclusions presented in Section 6. 2. Literature review 2.1. Drones and the Internet of drones (IoD) The emergence of Unmanned Aerial Vehicles (UAVs), commonly referred to as Drones, signifies a noteworthy technological advancement in aerial capabilities [6]. Operated remotely or autonomously and equipped with cameras and sensors, Drones serve various purposes such as aerial photography, surveying, logistics, and disaster management. Their utility extends to accessing challenging areas in both commercial and research domains [11,32]. Initially designed for military reconnaissance, Drones have expanded across diverse domains, categorized by operational zone (outdoor or indoor) and mission type (military or civil) [33]. In military contexts, Drones undertake critical operations such as missile launches, bomb deployment, battlefield surveillance, communications disruption, and medical supply delivery in combat zones. Civil applications include high-altitude Wi-Fi provision, aviation, delivery, videography, disaster response, environmental monitoring, construction, space exploration, inspection, maritime activities, meteorology, agriculture, and recreational use (M. [32,34–36]). Technological advancements have significantly expanded the capabilities of drones, making them versatile tools for diverse applications. Drones, equipped with high-resolution cameras, sophisticated sensors, and advanced flight controls, perform various tasks, including agricultural monitoring, environmental assessment, emergency response, and infrastructure inspection [4,37]. UAV applications in mining range from 2

mineral exploration to reclamation, highlighting their role in geological analyses and environmental monitoring [38]. Additionally, drones have become vital in forestry management, providing cost-effective, high-intensity data collection and operational flexibility, making them a formidable alternative to traditional remote sensing platforms [39]. Integrating artificial intelligence and the Internet of Things (IoT) has significantly enhanced drone capabilities, allowing for autonomous operations and real-time data processing (Yazdinejad et

al., 2021). UAVs play a transformative role by improving services in cellular communications, IoT networks, and disaster management through controlled mobility and adjustable altitudes [40]. Furthermore, advances in trajectory planning, strategic charging stations [41], and IoD simulator technology [42] optimize drone delivery systems and ensure their effective integration in shared airspace environments. The Internet of Drones (IoD) is an evolving network framework crucial for managing multiple Drones in shared airspace [43]. IoD dynamic network architecture enables improved communications and coordination between drones, offering significant advancements in applications ranging from critical mission services to environmental monitoring. It facilitates communication, navigation, and monitoring, enhancing efficiency and safety, which is particularly influential in manufacturing and collaborative operations [37,44]. The IoD has demonstrated substantial adaptability across diverse applications, enhancing network reliability, connectivity, and performance, crucial for its integration into sectors like agriculture, search and rescue, and surveillance [45]. In manufacturing, Drones encompass hardware, software, and support processes, integrating individual and collaborative functionalities [4]. The evolution from individual to collaborative functionalities in UAV technology underscores significant advancements in wireless communication and network protocols, reflecting a technological leap in UAV capabilities [37].

efficiency, crucial for scaling production [54]. In response to industrial accidents or natural disasters, drones rapidly assess and aid recovery, minimizing disruptions [11]. Along with Industry 4.0 principles, drones promote sustainable practices and reduce carbon emissions in last-mile delivery, offering a sustainable alternative to traditional transport methods [46]. Integrating machine learning with the Internet of Drones (IoD) enhances data collection and predictive modelling, improving decisionmaking in manufacturing [35]. IoD ensures the efficient and safe coordination of drone fleets [44] and optimizes manufacturing by enhancing performance parameters such as reliability and connectivity [45]. IoD Simulators allow manufacturers to explore advanced applications and improve operational planning [42]. Additionally, drones provide real-time insights into logistics within supply chain management, increasing efficiency and responsiveness [32,55]. 2.3. Barriers to the adoption of drones and IoD systems in manufacturing Integrating drones into manufacturing presents significant technical and operational challenges despite their potential. These include limited battery life of 2–25 min and difficulties in transporting heavy loads, complicating their use in continuous operations [6,8,10,40]. Indoor navigation is problematic for drones primarily designed for outdoor use, particularly in hazardous factory settings that require ATEX-certified drones [51,56]. Additionally, technical issues such as complex trajectory planning and the necessity for robust security measures pose significant barriers [41]. A fundamental challenge that Zhong et al. [27] identified is ensuring accurate localization and flight paths in indoor environments, where traditional sensor-based methods often fail, highlighting the need for innovative solutions like image-based flight control systems. The integration of Drones and the Internet of Drones (IoD) into manufacturing introduces substantial operational changes and incurs significant costs, further complicated by concerns over data privacy and susceptibility to cyberattacks [34,57–59]. The risk of data leakage heightens if someone commands drones [60]. Operational challenges include intricate drone scheduling and flight path optimization, which are critical to enhancing efficiency [54]. Multi-UAV systems in cyber-physical applications confront design challenges such as energy-efficient navigation and integrating machine learning for image analysis, which limit their adoption in manufacturing and related sectors [59]. Additionally, internal physical obstacles and worker fatigue complicate drone operations, while the essential development of advanced collision avoidance systems remains a significant barrier to reliable and safe UAV integration in manufacturing settings [6,31,61]. Challenges such as communication losses and data errors occur when multiple drones operate simultaneously, necessitating investment in advanced technologies like 5G and intelligent routing systems for reliable data transfer ([37]; Yazdinejad et al., 2021). Effective airspace management architecture is crucial for managing drone traffic and avoiding conflicts ([43]; S. [62]). Moreover, integrating the Internet of Drones (IoD) and drones for indoor navigation in confined manufacturing spaces raises concerns about data protection [31]. The reliability of drones poses challenges, with failure rates around 25 %, highlighting the need for rigorous maintenance [21,63]. Additionally, the absence of robust IoD simulators underscores significant issues in network management and performance evaluation, which are essential for optimizing drone deployment and operational efficiency in manufacturing [42]. Safety concerns in obstacle-dense industrial spaces, especially near human workers, highlight the need for skilled pilots and comprehensive training to minimize human error [10,64,65]. Jeelani and Gheisari [22] highlight the critical safety challenges associated with integrating UAVs into the construction industry, noting the lack of

comprehensive research on the impact of UAVs on worker health and safety. The accountability issue in Drone-related accidents remains unresolved,

2.2. Transformative potential of drones and IoD in manufacturing Drones have significantly transformed logistics and supply chain management, notably in imaging, monitoring, and inspection tasks [26, 31]. UAVs have been instrumental in reducing delivery times and operational costs in last-mile delivery, offering a cost-effective alternative to traditional methods [46]. Major companies like Amazon and FedEx have incorporated drones extensively, with Amazon now utilizing drones for over 83 % of its light orders, dramatically enhancing operational efficiency [43]. In the manufacturing sector, Drones and the Internet of Drones (IoD) are increasingly enhancing operational efficiency [47]. Drones, equipped with sensors, cameras, and data tools, are crucial for accessing difficult areas, monitoring processes, inspecting infrastructure, and managing inventory [48]. Mourtzis et al. [31] discuss UAVs' efficacy in indoor settings, utilizing Augmented Reality for path planning, which enhances decision-making and operational efficiency. Additionally, their role in predictive maintenance is vital, providing data that minimizes downtime and extends equipment life [12]. Drones significantly enhance manufacturing asset tracking and inventory management, utilizing RFID technology to optimize processes in large complexes [21,49]. They facilitate substantial improvements in inventory management, intra-logistics, inspections, and surveillance within smart warehouses, offering socio-economic benefits and a competitive edge [50]. Additionally, drones are crucial for inspecting complex structures, implementing thermal imaging for equipment monitoring, and enhancing safety in hazardous environments and search and rescue operations [4,51,52]. Drones play a critical role in energy management by monitoring usage to support efficient strategies and enhancing safety through compliance and hazard identification [35,53]. They automate inventory management in large warehouses, reducing labour and errors [50], and advanced scheduling solutions optimize logistics and operational 3

emphasizing the necessity for research to ascertain Drones' safety and reliability in industrial applications [6]. The substantial initial financial investment for Drone technology, including procurement, setup, and maintenance, poses challenges for small and medium-sized enterprises [35,36,59]. Furthermore, a robust network infrastructure is essential for effective IoD operation, representing a significant investment [40,53]. Scaling Drone operations for larger manufacturing tasks is economically challenging, particularly for smaller manufacturers [37,40,47]. The regulatory landscape for drones is evolving, marked by strict airspace regulations and privacy concerns that vary regionally, complicating compliance for manufacturers [66,67]. Lee et al. [25] highlight the disparity between well-developed safety regulations focusing on technical specifications and the less developed privacy regulations that fail to address UAV-specific challenges, presenting a significant barrier to broader UAV adoption. In many developing countries, the absence of explicit rules for commercial drone usage poses challenges for organizations aiming to legitimize drone applications [10]. Sociocultural factors such as perceptions of drones as substitutes for human roles and concerns over personal information security also hinder drone integration [51,68,69]. Additionally, the development of Advanced Air Mobility highlights the need for a multi-level governance model and a comprehensive policy framework for integrating environmentally friendly drones, reflecting broader challenges in adopting Drones and Internet of Drones (IoD) systems in manufacturing [23]. Concerns about reduced human interaction and unauthorized data collection also raise privacy issues, affecting worker acceptance of drones [70].

Table 1 Summary of barriers to Drones and IoD systems adoption in manufacturing. S/ N

Barriers

Explanation of Barriers

Sources

1

Limited battery capacity

[4,10,71]

2

High cost of Drone systems

3

Challenges with government regulations

4

Socially unacceptable

5

Noise

6

Data leakage

7

Lack of skilled pilots and operators

The barrier hinders extended operational periods for drones as their batteries can only store a limited amount of energy, often limiting flight times to 20–25 min. This constraint necessitates frequent recharging, thereby reducing the active usage time of Drones and adversely affecting the efficiency of manufacturing operations. The high cost of Drone systems encompasses not only the initial acquisition and implementation expenses of Drones in manufacturing but also the significant costs associated with supporting communication systems, ensuring reliable data transfer, providing highspeed internet, and conducting comprehensive training programs. The barrier refers to the complexities and uncertainties manufacturers face due to the lack of standardized and clear governmental guidelines governing Drone usage, especially in developing countries. These barriers include navigating varying regional laws and compliance issues, The barrier reflects societal resistance to Drones in manufacturing, stemming from concerns about job security, privacy invasion, and the intrusive nature of Drones. The barrier refers to the significant auditory disruption caused by Drones during operation, which can impact the work environment. This noise can affect communication and overall ambience in manufacturing settings. The barrier addresses the risk of unintentionally exposing or accessing sensitive information through Drones and IoD in manufacturing. This concern highlights vulnerabilities in data security, potentially leading to cyber threats and loss of confidential information. The barrier highlights the difficulty of finding adequately trained personnel to operate drones and IoD systems in manufacturing. The shortage of skilled professionals can impede the effective implementation and operation.

- Research methodology This study meticulously reviewed contemporary literature to decipher the complexities inhibiting the assimilation of Drones and IoD systems in the manufacturing industry. The review was executed across multiple reputed databases, such as Emerald, Elsevier, Springer, Wiley, Sage, Taylor & Francis (T&F), Inderscience, Google Scholar, IEEE, EBSCO, Scopus, and ISI Web of Science, leveraging a comprehensive set of keywords and phrases. The systematic literature review strategy encapsulated terms like “Unmanned Aerial Vehicles”, “UAVs”, “Drones”, “Internet of Drones”, “IoD”, “Barriers”, “Obstacles”, “Challenges”, “Impediments,” “Application of Drones in Manufacturing”, “Drone Technology”, “Drone Applications”, “Barriers to Drone Adoption in Manufacturing”, “Challenges in Implementing IoD in Manufacturing” and “Integration of Internet of Drones in Production”. Boolean operators, precisely “AND”, “OR”, and “NOT”, were judiciously deployed, fine-tuning the search outputs to enhance precision and relevance. Additional phrases, notably “Regulatory Compliance of Drones”, “Technological Limitations of Drones”, “Battery Life Limitations of Drones”, and “Drone Security”, “Drone Security”, and “Noise pollution using Drones”, further enriched the search paradigm. The collated literature underwent rigorous evaluation, initiating with a preliminary abstract analysis and culminating in an in-depth perusal of pertinent full-text articles. This thorough methodology, underpinned by academic exactitude, facilitated a holistic comprehension of barriers, blending scholarly and pragmatic vantage points. After this literary exploration, we designed a structured questionnaire and meticulously validated it with industry and scholarly authorities to confirm its robustness. Utilizing convenience sampling, we collected data, optimizing accessible demographics and data sources. The instrument underwent beta testing to ensure clarity and consistency before broad-scale deployment. Table 1 presents the barriers discerned from the literature. As shown in Fig. 1, the research methodology followed a tripartite structure to

investigate the Drone and IoD adoption barriers in manufacturing. An extensive literature review initially yielded 20 potential barriers, see Table 1. The subsequent phase involved an empirical

[6,37]

[6,10]

[10,51,72]

[4,37]

[57,60]

[6,10]

(continued on next page)

Table 1 (continued)

Table 1 (continued)

S/ N

Barriers

Explanation of Barriers

Sources

S/ N

Barriers

Explanation of Barriers

Sources

8

Insurance uncertainty in the event of a crash

[73]

15

The risk of damaging assets and people

An inability to carry a large amount of weight

16

The complexity of integrating the Drones and Internet of Drones

10

A time-consuming process for integrating Drones

17

Long battery charging time

18

Lack of ATEX-certified Drones

19

Risk of explosion

20

High failure rate

The barrier underscores the potential for Drones to interfere with manufacturing assets and personnel, posing a risk of damage and harm. This barrier necessitates robust airspace management and safety measures to mitigate collision risks. The barrier highlights the intricate nature of assimilating these technologies within multifaceted manufacturing operations. This complexity poses challenges in coordinating and synchronizing the various components of Drone systems and the Internet of Drones, requiring meticulous planning and technical expertise for successful integration. The barrier underscores the extended periods required for recharging Drone batteries after depletion, often exceeding an hour. This prolonged charging time leads to operational delays and affects the time efficiency of Drone utilization in continuous industrial operations. The barrier highlights the absence of Drones for safe operation in hazardous environments containing flammable substances, where ATEX compliance is essential. This limitation restricts their usability in critical industrial settings and calls for developing specialized drones to meet safety requirements. The barrier underscores the potential danger of Drone operations in manufacturing environments containing flammable materials, such as oil, petrol, and wood, which can lead to detonation hazards. Mitigating this risk is crucial for ensuring the safety of both personnel and assets in such settings. The barrier highlights the significant impact of suboptimal maintenance practices on Drone reliability, with failures occurring in approximately 25 % of cases. Addressing this challenge is essential to ensure Drones' consistent and safe operation within manufacturing environments.

[26,31]

9

The barrier refers to the ambiguity and complexities surrounding insurance coverage and claims for Drones in manufacturing, particularly after accidents. This uncertainty creates challenges in risk management and liability determination. This barrier pertains to the limited payload capacity of current Drone models, which restricts their ability to transport heavier or bulkier items in manufacturing settings. This limitation hampers the scalability and applicability of Drones for more extensive and varied industrial tasks. The barrier relates to the extensive duration and complexity of seamlessly incorporating Drones into existing manufacturing systems. The challenges include developing compatible workflow navigation algorithms and ensuring proper synchronisation with current operations. The barrier highlights the spatial constraints posed by machinery, structural elements, and safety installations, limiting the operational scope of Drones in manufacturing-settings. The barrier refers to the challenges Drones face in navigating complex manufacturing environments. The challenge includes difficulties in manoeuvring around obstacles and maintaining consistent flight paths, which are crucial for effective and safe Drone operations. The barrier arises from the high mobility of Drones, which can lead to challenges in data upload and download processes. These mobilityrelated issues can result in interrupted or incomplete data transmission, affecting the efficiency of Drone operations. The barrier highlights the challenges in multi-drone scenarios, where inter-drone communication may face hindrances. Other machinery and robots could also interfere with the transmission of Drones, leading to potential data inaccuracies or complete data loss, which in turn impacts the effectiveness of coordinated Drone operations.

11

12

13

14

Limited flying area

Insufficient navigation accuracy

Poor data transfer

Poor communication between Drones

([5]; Choi & Schonfeld, 2021; [10])

([6,73]; Li et al., 2020)

[4,31]

[4,51]

[4,37,74]

[6,31,37]

[6,31,74]

[6,10,21]

[75]

[6,73]

[63]

inquiry through a quantitative survey, collating insights from 120 global manufacturing industry professionals. This data underwent an EFA to validate and categorize the barriers. The culminating stage adopted the AHP technique for a hierarchical barrier ranking. The following sections 5

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Fig. 1. Research methodology stages.

detail this methodology, accentuating its potential for replication in subsequent similar investigations.

Table 2 Description of survey questions.

3.1. Data collection and analysis A survey questionnaire harvested expert perspectives, subsequently facilitating the validation of the barriers and categorisation into coherent clusters via an EFA. We then used the AHP technique to rank the barriers, drawing upon feedback from an expert panel. The survey was disseminated through email and LinkedIn, capitalizing on a diverse network of scholars and practitioners. This approach followed the suggested 5:1 ratio of respondents to variables for EFA, as Reio and Shuck [76] outlined, which indicated that we needed to obtain a minimum of 100 responses. Post-collection data underwent stringent cleaning, coding, and validation. This approach is consistent with the methodologies outlined in previous literature [77].

Question Category

Questions

Significance

Demographic

What type of manufacturing industry does your organisation belong to? Please specify the size of your organisation Which region is your organisation located in? Has your organisation ever used Drones or the IoD in the manufacturing process? Please rate the following barriers and their significance in adopting Drones and IoD in manufacturing. (1- Not important; 2- Moderately Important; 3- Important; 4Very Important; 5Extremely Important)

The questions provided a deeper understanding of the participants' industrial backgrounds, allowing for a more thorough examination of the data.

Importance Rating of Barriers on a 5point Likert scale

3.2. Survey instrument design To align with the principles established by Nardi [78], we formulated a structured questionnaire to guarantee valid and reliable data collection. The questionnaire comprised two segments: demographics and a detailed exploration of the 20 barriers, see Table 1, related to Drone and IoD adoption in manufacturing. The first segment of the questionnaire aimed to gather demographic details, focusing specifically on the respondents' industry background and expertise. In the second segment of the questionnaire, the primary research section asked participants to assess 20 impediments associated with drone and IoD integration in manufacturing, using a Likert scale anchored at 1 (Not Important) and culminating at 5 (Extremely Important). Table 2 outlines both sections.

These questions gave insights into professionals' views on the primary obstacles to adopting Drones and IoD in the manufacturing industry. The validation and analysis of this data helped to answer RQ2 and RQ3.

- Analysis and results 4.1. Demographic analysis In examining respondent demographics, this study evaluated four salient criteria: industry type, organisational size, geographical location, and organisational

experience in using Drones and IoD systems in the manufacturing processes. This selection was grounded in expert recommendations for survey face validity and paralleled methodologies 6

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documented in prior research [79]. Table 3 presents the demographic distribution of 120 valid survey responses, categorized by industry, size, region, and drone usage experience, crucial for this study's findings.

Table 4 Reliability test outcome of survey data.

4.2. Data cleansing and coding Rigorous data cleaning and coding procedures were employed to maintain data integrity during the analyses. Out of the initially received 138 responses, 120 were considered suitable for further examination after a stringent review for data completeness and accuracy. The number of participants exceeded the projected sample size of 100, as specified in Section 3.1. Notably, the attained sample size is comparable to, and even exceeds, those observed in other studies that have employed EFA [80]. We denoted demographic questions as 'DMa', referring to Table 3, and tagged questions concerning barriers as 'Ba', as shown in Table 4.

Mean

SD

B1 B2 B3

Limited battery capacity High cost of Drone systems Challenges with government regulations Socially unacceptable Noise Data leakage Lack of skilled pilots and operators Insurance uncertainty in the event of a crash An inability to carry a large amount of weight A time-consuming process for integrating Drones Limited flying area Insufficient navigation accuracy Poor data transfer Poor communication between Drones The risk of damaging assets and people The complexity of integrating the Drones and Internet of Drones Long battery charging time Lack of ATEX-certified Drones Risk of explosion High failure rate

0.768 0.766 0.765

3.97 3.61 4.09

0.987 1.056 1.053

0.76 0.758 0.757 0.753

2.88 2.39 3.97 3.73

1.089 1.132 1.144 1.053

0.755

2.91

1.202

0.772

3.78

1.063

0.769

3.22

1.006

0.765 0.759

3.41 3.25

0.992 1.055

0.755 0.754

2.83 2.92

1.042 1.12

0.758

4.32

1.021

0.757

3.45

0.839

0.767 0.764 0.757 0.754

3.03 2.69 3.78 3.32

1.334 1.419 1.24 1.069

B9 B10 B11 B12 B13 B14 B15 B16 B17 B18 B19 B20

Exploratory Factor Analysis (EFA). This validation ensures the survey's adequacy in capturing critical insights into drone and IoD integration challenges within the manufacturing sector. The survey's validity was corroborated through correlation with relevant scholarly literature, ensuring content validity. A panel of six experts, comprised of individuals from both academic and industrial sectors, conducted a pilot test to establish face validity. This panel included three academic experts with over fifteen years of experience and three drone experts with at least a decade of experience. Their feedback prompted minor adjustments, ultimately confirming the survey's suitability. Discriminant validity was further verified by applying Pearson's Correlation Coefficient. Table 5 displays Pearson Correlation coefficients from an analysis that examines interrelationships among barriers to adopting drones and Internet of Drones (IoD) systems labelled B1 through B20. This analysis reveals the strength and direction of relationships between these barriers, indicating the extent of their interdependence. The coefficients range from weak to moderate, all below 0.6, suggesting that while some barriers are related, they largely represent distinct aspects of adoption challenges [82]. This heterogeneity in correlations highlights the diversity of obstacles, emphasizing the need for a comprehensive strategy to tackle the complex challenges in Drone and IoD adoption. Table 4 presents the results of the descriptive analysis, where mean values exceeded the threshold of 2.5, underlining the significance of the barriers and thereby justifying their inclusion in the EFA [81].

Table 3 Demographic analysis of survey data. Variables

Received Responses

Frequency

Per cent

DM1: Industry

Aerospace and Defence Manufacturing Agricultural Manufacturing Automotive Construction Energy and utilities manufacturing Chemical and pharmaceutical manufacturing Electronics Food and beverage manufacturing Heavy machinery and equipment manufacturing Others Total Large (more than 250 employees) Medium (50–250 employees) Small (less than 50 employees) Total Asia Pacific Europe South America Middle East North America Africa Total Yes, currently Yes, in the past Never used, but intending to use Total

51

42.5

12 9 9 9

10 7.5 7.5 7.5

7

5.8

5 5

4.2 4.2

4

3.3

9 120 23

7.5 100 19.2

39 58 120 41 36 19 11 8 5 120 82 17 21 120

32.5 48.3 100 34.2 30 15.8 9.2 6.7 4.2 100 68.3 14.2 17.5 100

DM4: Experience in Drones and IoD

Cronbach's Alpha if Item Deleted

B8

To uphold the reliability of the data, we instantaneously captured responses via a survey platform and safeguarded them on a drive secured by password protection. The collected data, identified by variable codes B1 through B20, were subjected to a reliability assessment using Cronbach's Alpha. This present cross-sectional study confirmed the reliability of its survey with a Cronbach's Alpha of 0.77, surpassing the accepted threshold of 0.7, which underscores satisfactory internal consistency among the survey items [81]. The data, coded from B1 through B20, underwent a rigorous reliability assessment to ensure the robustness of the findings related to the barriers to adopting drones and Internet of Drones (IoD) systems. Table 4 presents the Alpha values for each surveyed barrier, alongside their mean and standard deviation, demonstrating that all items exceed the 0.7 benchmark for internal consistency. Moreover, mean values exceeding 2.5 highlights the significance of these barriers, validating their examination in the

DM3: Region

Adoption Barriers

B4 B5 B6 B7

4.3. Assessment of reliability and validity

DM2: Organisation Size

Variable

4.4. Structural analysis of Drone and IoD adoption barriers Table 6 evaluates the dataset's suitability for Exploratory Factor Analysis (EFA) using the Kaiser-Meyer-Olkin (KMO) measure, Bartlett's Test of Sphericity, and Cronbach's Alpha to ensure the data's reliability and appropriateness for analysis. The KMO measure achieves a value of 0.685, surpassing the recommended threshold of 0.6, confirming data adequacy for EFA [83]. Bartlett's Test of Sphericity shows a significant result ($p < 0.001$), validating the variables' sufficient correlation for 7

0.034 0.230* 0.034 0.164 0.279** 0.187* 0.160 0.265** 0.002 0.256** 0.194* 0.160 0.216* 0.177 0.233* 0.271** 0.122 0.253** 0.276** 1 0.172 0.208* 0.108 0.197* 0.105 0.486** 0.429** 0.042 0.345** 0.080 0.034 0.098 0.125 0.071 0.455** 0.187* − 0.087 0.127 1

Approx. Chi-Square df Sig.

585.892 190 0.001(<) 0.77

df = degrees of freedom. Sig = Significance.

factor analysis [84]. Furthermore, a Cronbach's Alpha of 0.77 indicates robust internal consistency among the survey items, supporting the decision to proceed with EFA [82]. The second phase of this study utilized Exploratory Factor Analysis (EFA) to analyze the structure of barriers to drone and Internet of Drones (IoD) adoption, as shown in Table 7. This analysis grouped barriers (B1 to B20) into six distinct dimensions, representing 59 % of the total variance, which, while below the Yong & Pearce [85] criterion of 75 %, aligns with the 52 % average observed in similar studies [86] and meets the accepted threshold of over 50 % [87]. The principal component analysis identified six factors with eigenvalues over one, indicating significant dimensions within the dataset [79]. A Varimax rotation further refined these factors, ensuring clarity in the classification and adherence to standard factor loading thresholds [88,89]. The minimized cross-loadings confirmed the distinctiveness of each factor (M. [90]). This structured approach facilitated a clear

understanding of how barriers are interrelated and categorized based on their underlying characteristics, with factor loadings emphasizing the strength of associations within specific dimensions. The resultant EFA framework effectively categorized the barriers into coherent groups, addressing Research Question 2 (RQ2). We corroborated these findings' practical applicability and accuracy through industry consultations, with Table 8 detailing the refined barrier categories. This phase highlighted each barrier's interconnections and distinct nature and validated the analytical methodology employed, ensuring the findings' relevance to industry practices.

Note: The study did not incorporate significance levels for 2-tailed tests because there was no requirement for this data in the assessment.

B19

Cronbach's Alpha (No of items¼21)

0.137 0.053 0.002 0.035 0.154 0.017 0.252** 0.269** 0.212* 0.130 0.054 0.310** 0.213* 0.365** 0.007 0.223* 0.152 1

B18

Bartlett's Test of Sphericity

0.256** 0.200* 0.082 0.147 0.164 0.076 0.013 0.353 0.024 0.107 0.091 0.394** 0.300** 0.289** 0.187* 0.272** 1

B17

Kaiser-Meyer-Olkin Measure of Sampling Adequacy 0.685

0.130 0.172 0.019 0.265** 0.246** 0.095 0.236** 0.250** 0.016 0.182 0.171 0.252 0.139 0.148 0.186* 1

B16

Table 6 Kaiser-Meyer-Olkin (KMO), Bartlett's test of Sphericity and Cronbach Alpha.

0.023 0.155 0.231* 0.308** 0.015 0.383** 0.324** 0.099 0.188* 0.080 0.203* 0.090 0.218 0.207 1

B15

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0.074 0.093 0.028 0.219* 0.132 0.116 0.137 0.232 0.013 0.091 0.152 0.274** 0.549** 1

B14 B13

0.084 0.159 0.030 0.173 0.108 0.044 0.132 0.182* 0.004 0.149 0.240 0.376** 1 0.145 − 0.085 0.259** 0.108 0.107 0.042 0.013 0.336** 0.094 0.036 0.359** 1

B12

0.069 0.168 0.011 0.036 0.102 0.130 0.176 0.072 0.060 1 0.193* 0.051 0.010 0.216* 0.127 0.326** 0.097 0.101 1

B11 B10 B9 B8

0.031 0.203* 0.272** 0.158 0.243** 0.077 0.186* 1 0.177 0.197* 0.281** 0.270** 0.190* 0.453** 1 0.103 0.093 0.386** 0.233* 0.185* 1 0.095 0.249** 0.167 0.272** 1

B7 B6 B5

0.035 0.045 0.186* 1

B4 B3

0.132 − 0.051 1 0.012 1

B2 B1

1 B1 B2 B3 B4 B5 B6 B7 B8 B9 B10 B11 B12 B13 B14 B15 B16 B17 B18 B19 B20

Table 5 Correlation matrix of the barriers to drone and IOD adoption based on Pearson correlation coefficients.

0.057 − 0.039 0.004 0.273** 0.156 0.020 0.061 0.144 0.188* 0.014 1

B20

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4.5. Hierarchical prioritization of drones and IoD adoption barriers in manufacturing The AHP provides a structured framework for dissecting complex decisions, incorporating essential tiers like objectives, criteria, and subcriteria [79]. Although alternatives like ANP, ELECTRE, and TOPSIS exist, AHP's intuitiveness makes it preferable for comparative dilemmas [91]. AHP's unique hierarchical approach notably simplifies intricate tasks [92]. The AHP is a valuable tool for ranking subjective factors by facilitating paired comparisons, which aids decision-makers in determining optimal priorities [93]. Given its effectiveness in prioritising barriers, this research incorporated AHP to assess obstacles to Drone and IoD adoption in manufacturing. 4.5.1. Formulation of research objective and pairwise comparisons Initiating the AHP demands precise articulation of the research objective [93]. Luthra et al. [91] indicate that AHP does not mandate a large sample, for which the quality of expert input is vital. Consistent with prior studies, this research engaged five experts adept in Drones and IoD [77]. The participants in this study were professionals with substantial expertise in integrating UAV technology within the industrial manufacturing domain. Each possessed a minimum of a decade of professional engagement in Drone technology. Table 9 profiles these experts. The AHP aimed to determine global weights to rank Drone and IoD adoption barriers in manufacturing. The results of this hierarchical analysis, depicted in Fig. 2, highlight the relative importance of each barrier, and provide a clear visual representation of how these barriers interrelate and impact the adoption of drones in the context of 8

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Table 7 EFA framework for six distinct Barrier dimensions. Factors Variable

Barriers to Drone and IoD adoption

1

B6 Data leakage B19 Risk of explosion B7 Lack of skilled pilots and operators B15 The risk of damaging assets and people B14 Poor communication between Drones B13 Poor data transfer B18 Lack of ATEX-certified Drones B12 Insufficient navigation accuracy B2 High cost of Drone systems B20 High failure rate B5 Noise B16 The complexity of integrating the Drones and Internet of Drones B10 A time-consuming process for integrating Drones B3 Challenges with government regulations B8 Insurance uncertainty in the event of a crash B11 Limited flying area B4 Socially unacceptable B9 An inability to carry a large amount of weight B1 Limited battery capacity B17 Long battery charging time Eigenvalues Total variance explained (%)

2

0.771 0.736 0.681 0.643

3.918 19.59

0.763 0.76 0.562 0.519

2.446 31.81

3

0.675 0.583 0.531 0.519 0.503

1.541 39.52

4

0.717 0.64

1.381 46.42

5

0.777 0.595

1.291 52.87

6

0.414 0.801 0.587 1.225 59.0

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 8 iterations.

manufacturing settings. This prioritization is crucial for stakeholders aiming to address the most significant challenges first, thereby streamlining efforts towards enhancing drone adoption in manufacturing. The three-tier order includes the primary goal (Level I), barrier dimensions from EFA (Level II), and the 20 specific obstacles (Level III). The Five experts conducted pairwise comparisons among barriers using Saaty's nine-point scale [94].

Table 8 Categorisation of Barriers to Drones and IoD adoption in the manufacturing industry. Factor

Category

Barriers

1

Safety and Human Resource Barriers (SHR)

2

Communication and Technological Barriers (CT)

3

Financial and Operational Barriers (FO)

4

Legislation and Risk Barriers (LR)

5

Social and Regulatory Barriers (SR) Payload Capacity and Battery Barriers (PCB)

Data Leakage (SHR1) Risk of explosion (SHR2) Lack of skilled pilot (SHR3) The risk of damaging assets and people (SHR4) Poor communication between Drones (CT1) Poor data transfer (CT2) Lack of ATEX-certified Drones (CT3) Insufficient navigation accuracy (CT4) The high cost of Drone systems (FO1) High failure rate (FO2) Noise (FO3) The complexity of integrating Drones and the Internet of Drones (FO4) A time-consuming process for integrating Drones (FO5) Challenges with government regulations (LR1) Insurance uncertainty in the event of a crash (LR2) Limited flying area (SR1) Socially unacceptable (SR2) An inability to carry a large amount of weight (PCB1) Limited battery capacity (PCB2) Long battery charging time (PCB3)

6

4.5.2. Calculation of relative weights and evaluating consistency ratio This study employed the AHP to aggregate expert pairwise comparison data, determining the relative importance of barriers to drone adoption in manufacturing. The results, displayed in Table 10, utilize the median as the aggregation method for its robustness against outliers. Table 10 outlines the pairwise comparison matrix with relative weights for the six main barrier dimensions identified through EFA. The relative importance of each dimension is quantified, leading to a ranked order based on their impact on based on their effect on drone adoption in manufacturing.

- Safety and Human Resource Barriers (SHR) are deemed the most significant, with a weight of 0.3377, reflecting the critical role of addressing safety concerns and human resources in supporting drone integration.
- Payload Capacity and Battery Barriers (PCB) follow with a weight of 0.2335, highlighting the technological challenges related to carrying capacity and battery life as substantial deterrents.
- Financial and Operational Barriers (FO) receive a weight of 0.1455, indicating concerns about drone technology's costs and operational effectiveness.
- Legislation and Risk Barriers (LR) receive a weight of 0.0971, suggesting these are significant yet manageable factors affecting adoption.
- Social and Regulatory Barriers (SR), with a weight of 0.0932, and Communication and Technological Barriers (CT) at 0.0929, represent less immediate but still noteworthy barriers affecting drone adoption.

Table 9 Drone expert panel for AHP. Expert

Position

Location

Work Experience (Years)

1 2 3 4 5

Systems Engineer Drone Pilot Drone Developer CEO Drone Consultant

EMEA USA Netherlands United Kingdom Brazil, Europe, APAC

14 17 14 26 21

To ensure the reliability of the Analytic Hierarchy Process (AHP) rankings, we calculated the consistency ratio (CR) for each pairwise comparison matrix, adhering to the threshold of CR ≤ 0.2, as 9

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Fig. 2. Drone and IoD adoption barriers to decision hierarchy. Table 10 Pairwise comparison matrix of the six main barriers and their relative weights. Major Barrier Dimensions

SHR

CT

FO

LR

SR

PCB

Relative Weight

Rank

Safety and Human Resource Barriers (SHR) Communication and Technological Barriers (CT) Financial and Operational Barriers (FO) Legislation and Risk Barriers (LR) Social and Regulatory Barriers (SR) Payload Capacity and Battery Barriers (PCB)

1 0.14 0.14 0.25 0.5 2

7 1 1 1 0.5 4

7 1 1 0.25 1 1

4 1 4 1 1 1

2 2 1 1 1 2

0.5 2.5 1 1 0.5 1

0.3377 0.0929 0.1455 0.0971 0.0932 0.2335

Ist 6th 3rd 4th 5th 2nd

recommended by Pauer et al. [95]. This level indicates a reasonable consistency among expert judgments. We occasionally asked experts to revise their responses to meet this criterion, ensuring that the final priorities reflected a logical and coherent assessment. Our rigorous approach to verifying consistency affirmed the reliability of our findings, enabling a confident identification of the most critical barriers to drone adoption. The outcomes, detailed in Table 11,

provide a hierarchical breakdown of specific obstacles within each dimension, organized by their relative weights and global ranks.

- Safety and Human Resource Barriers (SHR): The risk of explosion (SHR2) is the most critical, highlighting the urgent need for robust safety protocols. Other significant barriers include data leakage (SHR1) and lack of skilled pilots (SHR3), which emphasize concerns

Table 11 Ranking of Drones and IoD adoption barriers in the manufacturing industry. Dimension of Barriers

Relative Weights

Barriers

Relative Weights

Relative Rank

Global Weights

Global Rank

Safety and Human Resource Barriers (SHR)

0.3377

Communication and Technological Barriers (CT)

0.0932

Financial and Operational Barriers (FO)

0.1455

Data Leakage (SHR1) Risk of explosion (SHR2) Lack of skilled pilot (SHR3) The risk of damaging assets and people (SHR4) Poor communication between Drones (CT1) Poor data transfer (CT2) Lack of ATEX-certified Drones (CT3) Insufficient navigation accuracy (CT4) The high cost of Drone systems (FO1) High failure rate (FO2) Noise (FO3) The complexity of integrating Drones and the Internet of Drones (FO4) A time-consuming process for integrating Drones (FO5) Challenges with government regulations (LR1) Insurance uncertainty in the event of a crash (LR2) Limited flying area (SR1) Socially unacceptable (SR2) An inability to carry a large amount of weight (PCB1) Limited battery capacity (PCB2) Long battery charging time (PCB3)

0.0888 0.3365 0.2564 0.3184 0.1383 0.5146 0.2112 0.1359 0.1803 0.5075 0.0439 0.0488

4th 1st 3rd 2nd 3rd 1st 2nd 4th 3rd 1st 5th 4th

0.029971 0.113619 0.08653 0.107508 0.012854 0.047826 0.019630 0.012628 0.026229 0.073846 0.006384 0.007097

12th 2nd 5th 3rd 17th 9th 14th 18th 13th 6th 20th 19th

0.2246

2nd

0.032686

10th

0.7292 0.1458 0.3333 0.6667 0.4353 0.4866 0.0782

1st 2nd 2nd 1st 2nd 1st 3rd

0.070835 0.014167 0.031075 0.062151 0.101650 0.113626 0.018254

7th 16th 11th 8th 4th 1st 15th

Legislation and Risk Barriers (LR)

0.0971

Social and Regulatory Barriers (SR)

0.0932

Payload Capacity and Battery Barriers (PCB)

0.2335

10

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over information security and the need for specialized drone operation skills.

- Payload Capacity and Battery Barriers (PCB): Limited battery capacity (PCB2) ranks as the primary concern, followed by the inability to carry significant weight (PCB1) and long battery charging times (PCB3), pointing to necessary technological improvements in battery efficiency.
- Financial and Operational Barriers (FO): High failure rates (FO2) top this category, alongside challenges in drone integration (FO5) and the high cost of drone systems (FO1), reflecting economic and operational feasibility issues.
- Legislation and Risk Barriers (LR): Challenges with government regulations (LR1) are the foremost legislative barriers, followed by insurance uncertainties in the event of a crash (LR2), which underscore the financial and operational risks.
- Social and Regulatory Barriers (SR): Social acceptability (SR2) and limited flying areas (SR1) are primary concerns, indicating essential areas for improvement to enhance drone integration.
- Communication and Technological Barriers (CT): Poor data transfer (CT2) is the leading issue, followed by the lack of ATEX-certified drones (CT3) and poor inter-drone communication (CT1), highlighting the importance of reliable and safe communication technologies.
- Discussion The research conducted an in-depth analysis of the barriers to integrating Drone technology and IoD in the manufacturing industry. 5.1. Dimension 1: Safety and Human Resources Barriers (SHR) Within the 'Safety and Human Resources Barriers (SHR)' dimension in drone integration in manufacturing, the 'Risk of explosion (SHR2)' emerges as the most critical, particularly in environments with flammable materials where drones may trigger explosions [4]. Addressing this includes adopting explosion-proof drone technology and stringent operational protocols to enhance safety. Technological innovations, such as volatile compound sensors, are recommended to halt operations in hazardous conditions pre-emptively, alongside industry-specific safety regulations and regular audits of drone operations. The second principal barrier, 'Risk of damaging assets and people (SHR4)', necessitates effective airspace management to prevent drone collisions with manufacturing assets and personnel. Advanced collisionavoidance technologies and robust geofencing systems, potentially managed by AI, are essential to mitigate risks. Regulatory frameworks should clearly define drone operational zones and timings to minimize interactions with personnel and infrastructure, supported by managerial practices establishing designated facility drone areas. The 'Lack of skilled pilots (SHR3)' highlights the need for technical expertise in drone operations. Utilizing drone simulators and simulation-based training environments incorporating virtual reality can enhance operator skills in a risk-free setting. Strategic educational partnerships are crucial to maintaining a supply of trained operators, supported by policies advocating for recognized drone piloting as a legitimate profession. Lastly, 'Data Leakage (SHR1)' identifies the susceptibility of dronecollected data to cybersecurity threats. Implementing advanced cybersecurity measures, such as encryption and secure transmission protocols, regular security audits, and robust data governance frameworks, is vital. We recommend establishing comprehensive data protection standards specific to drone operations to guide manufacturers and operators in securing data effectively. These barriers underscore the complex challenges of adopting drones in manufacturing, highlighting the need for focused strategies on safety, workforce development, and cybersecurity. Insightful policy development and practice adjustments are necessary to mitigate these risks, fostering the secure integration of drone technologies in manufacturing.

These aggregated results illustrate the complex factors influencing drone adoption in manufacturing. By prioritising these barriers, stakeholders can strategically address the predominant challenges, facilitating more effective integration of drone technology into manufacturing operations. Our study delineates primary and secondary obstacles in analyzing the barriers to drone adoption in manufacturing, providing a strategic framework for industry stakeholders. The most critical challenge identified is Limited Battery Capacity (PCB2), highlighting the necessity for advancements in battery technology to enhance drone operational times and capabilities, which is crucial for sustained and efficient drone use. Innovations such as higher-density battery materials or solar-assist panels could significantly extend operational times, revolutionizing drone utility in continuous manufacturing operations and setting new standards for energy efficiency in drone technologies. The Risk of Explosion (SHR2) closely follows, which underscores the need for stringent safety protocols and the development of explosionproof drone models using advanced materials and containment strategies. This

barrier could transform the risk profile of drones in industrial settings. The third significant barrier, the Risk of Damaging Assets and People (SHR4), emphasizes the need for enhanced safety standards and advanced sensory and autonomous decision-making technologies to mitigate risks to operations and personnel. The fourth critical barrier, the Inability to Carry a Large Amount of Weight (PCB1), affects the versatility of drones in demanding industrial applications that require heavier payloads. Addressing this, alongside the High Failure Rate (FO2), which ranks fifth, is essential for expanding drone applications and building manufacturer confidence. Reliability enhanced through predictive maintenance technologies powered by IoT and machine learning could preempt potential failures and improve operational efficiency. Conversely, the least impactful barriers include the Complexity of Integration (FO4) and Noise (FO3). Although these factors have a lower immediate impact, they underscore areas for operational improvement and broader acceptance of drone technology. Streamlining integration processes and developing quieter drones can lead to better operational harmony and facilitate the widespread adoption of drones in manufacturing. Ongoing research, collaboration between technology developers and industry stakeholders, and adaptive regulatory frameworks should underpin these efforts to keep pace with technological advances and evolving safety standards.

5.2. Dimension 2: payload Capacity and Battery Barriers (PCB) In the typology of barriers to drone integration, the ’Payload Capacity and Battery Barriers (PCB)’ category is pivotal. These barriers significantly impact drone technology, necessitating innovative solutions and policy revisions to boost operational efficiency and enhance capabilities. The primary barrier, ’Limited battery capacity (PCB2)’, underscores the energy sustainability issues in drone operations, affecting the operational duration and necessitating frequent recharging. Advancements in battery technology could offer higher energy density and quicker recharging capabilities. Managerial strategies might include optimizing battery use through strategic operation scheduling and exploring renewable energy sources for charging. Another significant constraint is the ’Inability to carry a large amount of weight (PCB1)’, with current drone models typically supporting payloads not exceeding 2.5 kg. This limitation restricts their use in broader industrial tasks, limiting the range of materials transportable by drones. Addressing this requires research into lightweight materials and enhanced propulsion systems to increase payload scalability. Collaborations with material scientists and engineers are essential to develop drone designs that can handle increased payloads. Hybrid 11

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propulsion systems combining electric motors with internal combustion engines or fuel cells could provide necessary lifting power and extend operational ranges beyond traditional battery limits. Furthermore, integrating robotic mechanisms for load handling and manipulation, such as robotic arms or grippers, could allow drones to manage dynamic load adjustments during flight, enhancing stability and carrying capacity. The ’Long battery charging time (PCB3) barrier introduces significant operational delays. Innovations like lithium-ion batteries with advanced cathode materials or supercapacitors could reduce charging times drastically. Battery swapping stations and inductive charging systems could minimize downtime by allowing quick battery exchanges or wireless charging during brief landings. Integrating solar panels could extend operational times between charges, and smart scheduling algorithms could optimize charging periods to maximize availability during peak operational times. Addressing these challenges involves embracing ongoing research and developments in battery technology and drone design. Innovations to improve power efficiency, explore alternative energy sources, and advance materials engineering could revolutionize drone payload and endurance capabilities, enhancing their operational range and effectiveness. Such technological advances are crucial for drones’ broader implementation and impact in the manufacturing sector and beyond.

manufacturing, two principal barriers emerge that challenge the widespread operational deployment and safety of drone technologies. The foremost challenge, ’Challenges with government regulations (LR1)’, underscores the lack of definitive regulatory frameworks in many developing countries, hindering the commercial deployment of drones. The current regulatory patchwork, often lagging behind technological advancements, poses significant barriers to the growth and utility of drones across various sectors [96]. We recommend establishing regulatory sandboxes to address these regulatory challenges, allowing drone companies to test their technology under supervised conditions. This initiative would enable regulators to evaluate technological impacts in real time, fostering adaptive frameworks that evolve with technological advancements. Moreover, creating flexible, technology-specific legislation is crucial, allowing for swift

adaptations without overhauling the entire system. Automated compliance systems are also essential, helping operators ensure continual adherence to flight restrictions, privacy norms, and safety regulations through real-time data monitoring. The second significant barrier, 'Insurance uncertainty in the event of a crash' (LR2), points to the ambiguities surrounding liability and insurance claims post-drone accidents. The immature state of drone insurance protocols complicates stakeholder navigation through postaccident liabilities, presenting risks to operators and businesses. Addressing this requires establishing industry-wide risk assessment standards and implementing advanced telematics to capture comprehensive operational data, thus aiding accurate risk evaluation. Furthermore, blockchain technology could create a transparent and immutable ledger for insurance transactions, enhancing trust and streamlining claims processing. Additionally, exploring usage-based insurance models could align premium costs more closely with drone usage, incentivizing operators towards best practices. A holistic approach is necessary to overcome these barriers. Regulatory frameworks must be adaptable and comprehensive to standardize drone operations globally and simplify compliance processes. For insurance, clear guidelines should detail the methods for liability, risk assessment, and claim handling to mitigate associated risks. Monitoring legislative developments and actively participating in policy discussions is imperative to influence drone-related regulations. Evaluating impacts on public safety, privacy, and operational risks is crucial, alongside public engagement, to educate people on drone benefits and risks, ensuring community support for their sustainable integration.

5.3. Dimension 3: Financial and Operational Barriers (FO) In the 'Financial and Operational Barriers (FO)' dimension, critical challenges hinder the effective deployment of drone technology in industrial settings. Notably, the 'High failure rate (FO2)' reflects the adverse effects of inadequate maintenance, reporting a significant 25 % failure rate in drone operations [63]. Addressing this necessitates rigorous maintenance protocols, predictive maintenance systems utilizing IoT technology, and advanced fail-safe mechanisms to enhance reliability and operational efficiency. The 'Time-consuming process for integrating drones (FO5)' underscores the complexity of developing navigation algorithms and ensuring robust data protection. Streamlined development processes, modular drone designs, and digital twins could significantly reduce integration times and improve data security. The 'High cost of drone systems (FO1)' indicates the substantial investments required to equip drones with efficient communication and data handling capabilities. Cost-effective technologies, economies of scale, and models such as drones-as-a-service could mitigate these financial burdens, spreading costs over time and reducing initial expenditures. The 'Complexity of integrating drones and IoD (FO4)' illustrates the difficulties of assimilating these technologies within complex manufacturing operations. Simplifying integration through modular designs, standardized communication protocols, and specialized software platforms can facilitate smoother transitions and lessen operational complexities. Lastly, 'Noise (FO3)' addresses the auditory disruptions caused by drones, which can impact workplace communication and the environment. Developing quieter drone models and implementing operational guidelines to minimize noise exposure is crucial. Overcoming these barriers through innovative technological solutions and strategic managerial policies is vital for enhancing the operational efficiency and cost-effectiveness of drone technology in manufacturing. These efforts can transform manufacturing processes and outcomes by addressing the specific needs and challenges within the sector.

5.5. Dimension 5: Social and Regulatory Barriers (SR) The dimension termed 'Social and Regulatory Barriers (SR)' emerges as the fifth critical area, embodying significant barriers to integrating drones across various settings. The first barrier, 'Social unacceptability (SR2),' underscores societal hesitance towards drones, fueled by concerns over job displacement, privacy violations, and integration into daily life. Addressing these requires robust public engagement initiatives to educate on drone benefits, address privacy concerns, and discuss potential employment impacts transparently. Community involvement in drone project planning and deployment fosters ownership and acceptance, enhancing societal acceptance. Partnering with local civic organizations, educational institutions, and non-profits is crucial for promoting the positive impacts of drones in emergency response and environmental monitoring. Additionally, establishing ethical standards and certification programs for drone operators will enhance their professional image and societal trust. The second barrier, 'Limited flying area (SR1),' highlights spatial constraints within manufacturing environments that restrict drone mobility, often complicated by obstructions like machinery and structural elements (Zhang & Ansari, 2019). Innovative design solutions are essential for improving drone manoeuvrability and agility. Advanced navigation systems that utilize AI and machine learning

5.4. Dimension 4: Legislation and Risk Barriers (LR) Within the 'Legislation and Risk Barriers (LR)' category, identified as the fourth most significant obstacle to drone integration in 12

can enable drones to autonomously navigate confined spaces, using dynamic obstacle detection and avoidance technologies to adjust flight paths. Deploying Indoor Positioning Systems (IPS) tailored for indoor environments enhances drone navigation capabilities within complex layouts. Utilizing Building Information Modeling (BIM) to create detailed 3D maps enables drones to plan optimal flight paths and navigate effectively. Implementing Virtual Reality (VR) simulations for drone operators facilitates training in virtual environments, which mirrors actual manufacturing settings, preparing operators for safe navigation in realworld operations. Furthermore, developing specific regulations tailored to indoor aviation ensures safe and effective drone operations within constrained environments. These efforts are vital for overcoming drones' spatial challenges in manufacturing and optimizing operational efficiency and effectiveness. This comprehensive approach involving technological innovations, managerial foresight, and policy adaptations is crucial for enhancing drone integration and acceptance within broader societal and manufacturing contexts.

Safety is paramount, particularly in environments with flammable materials, necessitating stringent protocols and ATEX-certified drones to ensure safe operational distances. Robust data security measures, including strong encryption and vigilant cyber defence strategies, are required. Furthermore, we advocate for comprehensive training and certification programs enriched with simulation-based exercises to enhance drone piloting proficiency, which is critical. We recommend using advanced antenna technologies to improve data transfer reliability. Financial and operational challenges require conducting cost-benefit analyses to find cost-effective solutions for drone maintenance and integration. Implementing Drone-as-a-Service (DaaS) models can minimize upfront costs and provide scalability. Streamlining integration with advanced algorithms can improve efficiency and investment returns. We advise performing regular maintenance every 100 flight hours to ensure drone reliability, which involves inspecting control, structural, payload, navigation, and electronic systems. Compliance with national regulations, including licensing and insurance, is essential. Industry leaders should engage with policymakers to create a favourable regulatory environment and establish clear insurance protocols. A flexible operational strategy is necessary to adapt quickly to new or evolving drone legislation. Public acceptance of drones demands transparent communication about their roles and benefits, alongside targeted personnel training. Developing public engagement initiatives is crucial to educate and inform the community about the benefits and safety of drone technology. Decisions on payload capacity should reflect operational needs, balancing delivery-oriented tasks with diverse functions. We require innovative solutions for navigating limited flying areas, such as designing custom drones for indoor use. Addressing battery life limitations involves strategically placing charging stations for rapid recharging. Investing in advanced communication and navigation technologies is crucial to enhancing the reliability and efficiency of drone operations. Adopting emerging technologies such as 5G can significantly improve drone communication capabilities. Developing contingency plans to manage communication failures ensures continuous operation during critical missions. Comprehensive policy implications are necessary to address the challenges posed by drone integration across various sectors. These should include developing industry-specific safety regulations and standards, particularly for operations in hazardous environments, and supporting innovation through subsidies and incentives for advanced drone technology research. Policies should also promote harmonising international drone regulations to facilitate global operations and ensure that legislation keeps pace with technological advancements. We recommend offering financial incentives such as tax breaks and grants to encourage investment in drone technology. Additionally, clear guidelines for drone integration into business operations are necessary to streamline adoption processes. To build public trust and acceptance, supporting public awareness campaigns and educational programs about the benefits and safety of drones while implementing robust privacy protections and data security measures to address societal concerns is crucial. Lastly, promoting the development of communication standards and protocols will enhance drone interoperability and safety, facilitating the adoption of new technologies such as 5G to improve communication capabilities in drone operations. These policy measures will collectively enhance the operational effectiveness, safety, and societal acceptance of drones in various industries.

5.6. Dimension 6: Communication and technological barriers (CT) Within the 'Communication and Technological Barriers (CT)' category, four barriers present distinct challenges in drone integration, with 'Poor data transfer (CT2)' identified as the primary concern. Inefficiencies in drone data exchange can be mitigated by developing advanced data transmission protocols, ensuring secure and reliable data flow in mobile scenarios (Zhang & Ansari, 2019). Enhancements such as dedicated communication channels and edge computing can streamline data handling, improving response times and reliability. The 'Lack of ATEX-certified Drones (CT3)' indicates a significant shortfall in drones certified for operation in hazardous environments. Addressing this barrier involves equipping drones with sensors for detecting volatile compounds and designing intrinsic safety features that prevent ignition in explosive atmospheres [97]. When combined with rigorous training and industry-specific regulations, these measures will enhance drone safety and compliance. 'Poor communication between Drones (CT1)' is another notable barrier, especially in multi-drone operations. Implementing mesh networking can enhance connectivity and resilience by allowing drones to form a dynamic network. Furthermore, employing advanced frequency management techniques and exploring quantum communication can bolster the security and efficiency of drone communications. The 'Insufficient navigation accuracy (CT4)' barrier, significant in indoor manufacturing settings, necessitates investments in advanced navigation systems such as LiDAR or ultrasonic sensors. Technologies like RTK GPS and visual odometry can enhance navigation precision, which is crucial in GPS-denied environments [59]. Additionally, integrating sensor fusion techniques and deploying Ultra-Wideband (UWB) technology can improve location tracking accuracy indoors. Addressing these challenges requires a multifaceted approach involving technological advancements, strategic management initiatives, and policy interventions. Engaging stakeholders in developing and enforcing safety and operational standards is crucial for fostering a conducive environment for advanced drone operations. Collectively, these efforts will enable drones to overcome communication and technological barriers, enhancing their integration and efficacy in manufacturing and other industrial settings.
5.7. Managerial and policy implications

- Conclusions

We must develop comprehensive managerial and policy frameworks to effectively integrate Drones and the Internet of Drones (IoD) within manufacturing ecosystems. These frameworks should address barriers that significantly impact the adoption processes, ensuring a detailed understanding of strategic planning and deployment.

In manufacturing, incorporating Drones and the IoD marks a significant step toward enhancing operational practices. This research delineates the challenges in adopting these technologies, contributing to filling a gap in the academic literature and seeking to improve our 13

- In-depth Examination of Specific Barriers: Future research should delve deeper into the underlying causes of each identified barrier, particularly examining the role of government policy and how variations between countries affect drone adoption in manufacturing.
- Comprehensive View of Adoption Barriers: A more comprehensive approach is needed to consider technical, infrastructural, economic, and political factors affecting drone and IoD system adoption. Manufacturers can explore integrating drones with advanced manufacturing processes to achieve efficiency and sustainability goals.
- Mixed Methods and Longitudinal Designs: Employing mixed methods and longitudinal study designs can provide a more dynamic understanding of the evolving nature of adoption barriers across different geographical, industrial, cultural, economic, and environmental contexts.
- Stakeholder Perceptions: Understanding the perceptions of different stakeholders through psychological and sociological analyses is vital. These analyses will help address the motivational and attitudinal drivers behind the adoption of drones in the manufacturing sector.
- Policy and Incentive Schemes: Investigating incentive schemes and policy interventions across various landscapes is crucial. This research could inform strategies to enhance drone adoption rates and sustainability outcomes.

theoretical knowledge and practical applications concerning the assimilation of these technologies in a manufacturing setting. The study theoretically contributes by identifying and categorising twenty barriers into six categories through an Exploratory Factor Analysis (EFA). Applying the Analytic Hierarchy Process (AHP) assigns a hierarchical structure to these challenges, providing a global perspective previously understudied in the scholarly literature. The research offers a structured framework of challenges across domains such as safety and human resources, communication, and technology, financial and operational, legislation and risk, social and regulatory, and payload capacity and battery. This ranking contributes to practice by informing industry stakeholders in strategising for effective Drone and IoD integration. The study's combination of empirical research with quantitative methodologies like EFA and AHP introduces an effective analytical perspective to understand the barriers to Drones and IoD integration in manufacturing contexts, benefiting practitioners in overcoming these obstacles. 6.1. Limitations and future research directions This study provides an in-depth analysis of the challenges associated with adopting drones and Internet of Drones (IoD) systems in manufacturing. Despite the comprehensive nature of the research, several limitations may affect the robustness and generalizability of the results.

CRediT authorship contribution statement

- Sampling Limitations: The primary limitation is the reliance on convenience sampling involving 120 global manufacturing industry experts. While efficient, this method may not capture the full diversity of manufacturing scenarios and geographic regions. As such, the results might be biased towards those already familiar with or interested in drone technologies, potentially excluding smaller enterprises or emerging markets.
- Geographical Representation: The geographic diversity within the sample is another limitation. The majority of experts might share similar experiences influenced by their regional market operations, which could reflect biases and limit the global applicability of the findings.
- Methodological Constraints: Exploratory Factor Analysis (EFA) and Analytical Hierarchy Process (AHP) introduce certain limitations. EFA depends on the initial choice and several factors that could affect the results. AHP, while structured, may introduce subjectivity through its pairwise comparison process and the potential bias of expert judgments.

Dauren Askerbekov: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. Jose Arturo Garza-Reyes: Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. Ranjit Roy Ghatak: Writing – review & editing, Validation, Investigation, Conceptualization. Rohit Joshi: Writing – review & editing, Visualization, Supervision, Conceptualization. Jayakrishna Kandasamy: Writing – review & editing, Visualization, Validation, Conceptualization. Daniel Luiz de Mattos Nascimento: Writing – review & editing, Visualization, Validation, Conceptualization. Data availability Data will be made available on request. References [1] L.S. Dalenogare, G.B. Benitez, N.F. Ayala, A.G. Frank, The expected contribution of Industry 4.0 technologies for industrial performance, Int. J. Prod. Econ. 204 (2018) 383–394, https://doi.org/10.1016/j.ijpe.2018.08.019. Scopus. [2] M. Ghobakhloo, Industry 4.0, digitization, and opportunities for sustainability, J. Clean. Prod. 252 (2020) Scopus, https://doi.org/10.1016/j. jclepro. 2019.119869. [3] A. Raj, G. Dwivedi, A. Sharma, A.B. Lopes De Sousa Jabbour, S. Rajak, Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: an intercountry comparative perspective, Int. J. Prod. Econ. 224 (2020) 107546, https:// doi.org/10.1016/j.ijpe.2019.107546. [4] O. Maghazei, T. Netland, Drones in manufacturing: exploring opportunities for research and practice, J. Manuf. Technol. Manag. 31 (6) (2019) 1237–1259, https://doi.org/10.1108/JMTM-03-2019-0099. [5] M. Ayamga, S. Akaba, A.A. Nyaaba, Multifaceted applicability of drones: a review, Technol. Forecast. Soc. Change 167 (2021) 120677, https://doi.org/10.1016/j. techfore.2021.120677. [6] O. Maghazei, M.A. Lewis, T.H. Netland, Emerging technologies and the use case: a multi-year study of drone adoption, J. Oper. Manag. 68 (6–7) (2022) 560–591, https://doi.org/10.1002/joom.1196. Scopus. [7] How Do Drones Help Farmers?, AUVSI, 2018. https://www.auvsi.org/how-do-dro nes-help-farmers. [8] H. Puppala, P.R.T. Peddinti, J.P. Tamvada, J. Ahuja, B. Kim, Barriers to the adoption of new technologies in rural areas: the case of unmanned aerial vehicles for precision agriculture in India, Technol. Soc. 74 (2023), https://doi.org/ 10.1016/j.techsoc.2023.102335. Scopus. [9] M. Moshref-Javadi, S. Lee, M. Winkenbach, Design and evaluation of a multi-trip delivery model with truck and drones, Transport. Res. E Logist. Transport. Rev. 136 (2020) 101887, https://doi.org/10.1016/j.tre.2020.101887. [10] A. Rejeb, K. Rejeb, S.J. Simske, H. Treiblmaier, Drones for supply chain management and logistics: a review and research agenda, Int. J. Logist. Res. Appl.

Given these limitations, the study suggests several areas for future research, outlined as follows.

- Enhanced Sampling Techniques: Future studies should utilize more robust sampling methods, such as stratified or random sampling, to improve the representativeness of the results and ensure they reflect a broader range of manufacturing contexts and regions.
- Integration of Additional Decision-Making Frameworks: To address the methodological constraints, incorporating decision-making frameworks such as the Delphi method or other multi-criteria decisionmaking (MCDM) techniques could balance the criteria weighting and reduce biases inherent in AHP.
- Conducting Sensitivity Analyses: A need exists for sensitivity analysis in future research to test the robustness of findings and explore how modifications to the analyzed barriers could influence proposed solutions. This analysis would also help understand the relative importance of the different obstacles under various scenarios.
- Periodic Updating of Findings: Given the rapid evolution in drone technology and regulatory frameworks, it is crucial to periodically update the research findings to ensure they remain relevant and reflect the current technology and market conditions. 14

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Detection and Tracking Meet Drones Challenge

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Abstract—Drones, or general UAVs, equipped with cameras have been fast deployed with a wide range of applications, including agriculture, aerial photography, and surveillance. Consequently, automatic understanding of visual data collected from drones becomes highly demanding, bringing computer vision and drones more and more closely. To promote and track the developments of object detection and tracking

algorithms, we have organized three challenge workshops in conjunction with ECCV 2018, ICCV 2019 and ECCV 2020, attracting more than 100 teams around the world. We provide a large-scale drone captured dataset, VisDrone, which includes four tracks, i.e., (1) image object detection, (2) video object detection, (3) single object tracking, and (4) multi-object tracking. In this paper, we first present a thorough review of object detection and tracking datasets and benchmarks, and discuss the challenges of collecting large-scale drone-based object detection and tracking datasets with fully manual annotations. After that, we describe our VisDrone dataset, which is captured over various urban/suburban areas of 14 different cities across China from North to South. Being the largest such dataset ever published, VisDrone enables extensive evaluation and investigation of visual analysis algorithms for the drone platform. We provide a detailed analysis of the current state of the field of large-scale object detection and tracking on drones, and conclude the challenge as well as propose future directions. We expect the benchmark largely boost the research and development in video analysis on drone platforms. All the datasets and experimental results can be downloaded from https://github.com/VisDrone/VisDrone-Dataset. Index Terms—Drone, benchmark, image object detection, video object detection, single object tracking, multi-object tracking.

F

I NTRODUCTION

D

RONES (or UAVs) equipped with cameras are receiving a lot of attention in recent years. The commercial drone market report [1] describes that the global commercial drone market size will reach 501.4 billion by 2028, with a compound annual growth rate of 57.5% from 2021 to 2028. Equipped with embedded devices, drones are able to analyze the captured data and spawn a variety of new application scenarios, e.g.,

- Agriculture. Drones can provide valuable insights to

help farmers or ranchers optimize agriculture operations, monitor crop growth and keep herds safe, etc.

- Aerial photography. Drones are used to extract aerial photography images instead of expensive cranes and helicopters.
- Shipping and delivery. Drones can efficiently send packages such as medical supplies, food, or other goods to the designated places.
- Security and surveillance. Drones can provide realtime visibility into security threats and emergency situations by monitoring large regions.

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- Search and rescue. Drones are useful to help search

missing persons, fugitives, or rescue survivors and drop supplies in difficult terrains and harsh conditions. Consequently, automatic understanding of visual data collected from drones become highly demanding, which brings computer vision to drones more and more closely. As two fundamental problems in computer vision, object detection and object tracking are under extensive investigation. However, although the great progress has been made in various application scenarios such as Internet and security surveillance, they are not usually optimal for dealing with drone captured sequences or images. Notably, comparing to existing datasets in computer vision field, the dronecaptured video sequences bring several new challenges, described as follows.

- Viewpoint variations: comparing to surveillance cameras

with fixed viewpoints, drone-equipped cameras monitor the objects in arbitrary viewpoints [2].

- Scale variations: drone-equipped cameras monitor the objects at different altitudes, resulting in large variations of scales of objects [3].
- Motion blur: videos are generally recorded by the droneequipped cameras in the moving process, bringing in considerable motion blurs of the recorded videos [4]. Thus, it is necessary to develop and evaluate new vision algorithms for drone captured visual data. However, as pointed out in [2], [5], studies toward this goal are seriously limited by the lack of publicly available large-scale benchmarks or datasets. Some recent efforts [2], [5], [6] have been devoted to construct datasets captured by drones focusing on object detection or tracking. These datasets are still limited in size and scenarios covered, due to the difficulties in data collection and annotation. Thorough evaluations of existing or newly developed algorithms remain an open

problem. A more general and comprehensive benchmark is desired for further boosting video analysis research on drone platforms. Thus motivated, we have organized three challenge workshops in conjunction with European Conference on Computer Vision (ECCV) 2018 [7], [8], [9], IEEE International Conference on Computer Vision (ICCV) 2019 [10], [11], [12], [13], and European Conference on Computer Vision (ECCV) 2020 [14], [15], [16], attracting more than 100 research teams around the world. The challenge focuses on object detection and tracking with four tracks.

- Image object detection track (DET). Given a pre-defined

set of object classes, e.g., cars and pedestrians, the algorithm is required to detect objects of these classes from individual images taken by drones.

- Video object detection track (VID). Similar to DET, the algorithm is required to detect objects of predefined object classes from videos taken by drones.
- Single object tracking track (SOT). The goal of the track is to estimate the state of a target, indicated in the first frame, across frames in an online manner.
- Multi-object tracking track (MOT). This track aims to localize object instances in each video frame and recover their trajectories in video sequences. Notably, in the workshop challenges, we provide a largescale dataset, which consists of 263 video clips with 179, 264 frames and 10, 209 static images. The data is recorded by various drone-mounted cameras, diverse in many aspects including location (taken from 14 different cities in China), environment (urban and rural regions), objects (e.g., pedestrian, vehicles, and bicycles), and density (sparse and crowded scenes). We select 10 categories of objects of frequent interests in drone applications, such as pedestrians and cars. Altogether we carefully annotate more than 2.5 million bounding boxes of object instances from these categories. Moreover, some important attributes including visibility of the scenes, object category and occlusion, are provided for better data usage. The detailed comparison of the provided drone datasets with other related datasets in object detection and tracking are presented in Table 1. Scope of this paper. This paper summarizes the VisDroneChallenges organized from 2018 to 2020, which is extended from the challenge summary papers [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. Note that the previous summary papers just briefly introduce the VisDrone dataset, enumerate the submitted methods, and report the evaluation results. In contrast, this paper focuses on analyzing various representative object detection and tracking algorithms thoroughly. Specifically, we discuss and analyze the advantages and disadvantages of the submitted methods in terms of model design and training strategies. After that, we advocate several future research directions of object detection and tracking on drone-captured videos. We expect such comprehensive review and analysis to largely boost the research and development in video analysis on drones. In summary, the focus of this paper is twofold, i.e.,
- A

new large-scale benchmark captured by droneequipped cameras is proposed for DET, VID, SOT and MOT, which provides a comprehensive evaluation platform for object detection and tracking.

- We discuss the technical trend based on the state-ofthe-art methods and forecast several potential research directions in this field.

R ELATED W ORK

2.1

Surveys and Related Challenges

Several survey papers are presented to discuss different topics in computer vision, such as generic object detection [37], single object tracking [38], and multi-object tracking [39]. Liu et al. [37] summarize more than 300 papers on generic object detection in terms of the detection framework, object feature extraction, object proposal generation, context modeling, training strategies, etc. In [38], the advantages and disadvantages of recent deep learning based trackers are investigated. Ciaparrone et al. [39] identify four main steps in multi-object tracking algorithms and present an in-depth review of the deep learning algorithms employed in each stage. In contrast to previous surveys solely focusing on generic object detection or tracking, we review and analyze the algorithms for object detection and tracking on dronecaptured videos, which is useful to provide researchers a reference and guidance for algorithm design. In recent years, several challenges are organized to promote the developments of algorithms in object detection and tracking. The international workshop on computer vision for UAVs1 focuses on hardware, software and algorithmic (co-)optimizations towards the state-of-the-art image processing strategies on UAVs. Similarly, the Lower Power Object Detection Challenge [40] focuses on designing and implementing efficient object detection methods for UAVs. The VOT workshop2 provides the tracking community with a precisely defined and repeatable way to compare shortterm trackers as well as provides a common platform for discussing the evaluation and advancements made in the field of single-object tracking. The BMTT and BMTT-PETS workshops3 aims to pave the way for a unified framework towards more meaningful evaluation of multi-object tracking. The Tiny Object Detection challenge4 opens an interesting but challenging task, i.e., tiny person detection in unconstrained environments. Different from the aforementioned challenges and workshops, our workshop challenge aims to promote the developments of object detection and tracking on drone-captured videos, formed by four tracks, i.e., DET, VID, SOT, and MOT. 2.2

Object Detection and Tracking Datasets

Image object detection datasets. There are several image object detection datasets [19], [34], [41], [42] constructed to promote the developments in related fields. PASCAL VOC [42] is one of the most popular benchmarks in generic object detection including 20 classes, e.g., person, aeroplane, car and tvmonitor. Recently, MS COCO [19] with 80 common object categories in real life, becomes the mainstream benchmark for object detection. It is more challenging than PASCAL 1. https://sites.google.com/site/uavision2018/. 2. http://www.votchallenge.net/. 3. https://motchallenge.net/. 4. https://rlq-tod.github.io/index.html.

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TABLE 1: Comparison of the existing benchmarks and datasets. Note that, the resolution indicates the maximum resolution of videos/images included in the benchmarks and datasets. (1k = 1, 000) Image object detection PASCAL VOC2012 [17] ImageNet Object Detection [18] MS COCO [19] COWC [20] CARPK [5] DOTA [21] MOR-UAV [22] VisDrone

scenario life life life aerial drone aerial drone drone

Video object detection ImageNet Video Detection [18] UA-DETRAC Detection [23] MOT17Det [24] Okutama-Action [25] UAVDT-DET [4] DroneSURF [3] VisDrone

scenario life surveillance life drone drone drone drone

#frames 2017.6k 140.1k 11.2k 77.4k 40.7k 411.5k 40.0k

categories 20 200 91 1 1 15 2 10 categories 30 4 1 1 3 1 10

scenarios life life drone drone drone life life drone life drone drone

Single object tracking OTB100 [26] VOT2016 [27] UAV123 [2] DTB70 [28] UAVDT-SOT [4] GOT-10k [29] TrackingNet [30] MDOT [31] LaSOT [32] Anti-UAV [33] VisDrone Multi-object tracking KITTI Tracking [34] MOT15 [24] UA-DETRAC Tracking [23] DukeMTMC [35] Campus [6] MOT17 [24] UAVDT-MOT [4] TAO [36] VisDrone

#images 22.5k 456.2k 328.0k 32.7k 1, 448 2, 806 10, 948 10, 209

scenario driving surveillance surveillance surveillance drone surveillance drone life drone

#frames 19.1k 11.3k 140.1k 2852.2k 929.5k 11.2k 40.7k 2674.4k 40.0k

avg. #labels/categories 1, 373 2, 007 27.5k 32.7k 89.8k 12.6k 44.9k 54.2k avg. #labels/categories 66.8k 302.5k 392.8k 422.1k 267.6k 786.8k 183.3k #sequences 100 60 123 70 50 10.0k 30.6k 373 1.55k 318 167

categories 5 1 4 1 6 1 3 833 10

VOC [42] due to several factors such as scale variations of objects, clutter background and heavy occlusion. Video object detection datasets. To advance the development of object detection in videos, ILSVRC [18] selects 30 categories of real-life objects for video object detection. The YouTube-Objects dataset [43] is another large-scale dataset collected from YouTube, which is formed by 9 ~ 24 annotated videos in 10 categories. Meanwhile, Wen et al. [23], [44], [45] collect the UA-DETRAC dataset in traffic scenarios for vehicle detection. The MOTChallenge team constructs the MOT17Det [24] and MOT20Det [46] benchmarks for pedestrian detection. Single object tracking datasets. Various datasets [26], [27], [47], [48], [49], [50], [51], [52], [53] are collected to facilitate the training and testing of single object tracking methods. Among them, OTB [26] is the precursor benchmark dataset designed to fairly evaluate the single object trackers. After that, VOT [27], [51], [52] becomes another popular benchmark for SOT evaluation, which includes rotated bounding box and visual attributes annotations in each frame. To evaluate the tracking accuracy of deformable objects, Du et al. [53] propose the Deform-SOT dataset with 50 sequences in unconstrained environments. To facilitate data-driven deep learning methods, more large-scale visual tracking datasets have been proposed in recent three years. GOT-10k [29] is collected by 563 classes of moving objects and 87 classes of motion to cover as many

avg. #labels/categories 19.0k 101.3k 302.5k 4077.1k 1769.4k 392.8k 267.6k 0.4k 183.3k

resolution 469 × 387 482 × 415 640 × 640 2048 × 2048 1280 × 720 12029 × 5014 1920 × 1080 2000 × 1500

occlusion labels √ √

resolution 1280 × 1080 960 × 540 1920 × 1080 3840 × 2160 1080 × 540 1280 × 720 3840 × 2160

occlusion labels √ √ √

√

√ √

#frames 59.0k 21.5k 110k 15.8k 37.2k 1500.0k 1443.1k 259.8k 3870.0k 585.9k 139.3k resolution 1392 × 512 1920 × 1080 960 × 540 1920 × 1080 1417 × 2019 1920 × 1080 1080 × 540 1280 × 720 3840 × 2160

year 2012 2013 2014 2016 2017 2018 2020 2018 year 2015 2015 2017 2017 2018 2019 2018

year 2015 2016 2016 2017 2018 2018 2018 2020 2021 2021 2018 occlusion labels √ √

√ √

year 2013 2015 2015 2016 2016 2017 2018 2020 2018

real-world scenarios as possible. Moreover, TrackingNet [30] includes more than 30K videos and more that 14 million bounding box annotations to cover a wide selection of object classes in broad and diverse context. The LaSOT [32] dataset provides a dedicated platform for training deep trackers and evaluating long-term tracking performance, to address the problems of small-scale, lack of high-quality dense annotations, short-term tracking, and category bias. Multi-object tracking datasets. Several multi-object tracking datasets are constructed to evaluate the MOT methods, including KITTI [34], MOTChallenge [24], and UA-DETRAC [23], [44], [45]. KITTI [34] is designed for autonomous driving scenarios. The MOTChallenge team establishes a unified platform to evaluate the multi-pedestrian tracking methods, including the MOT15 [24] and MOT16 [24] datasets. The UA-DETRAC dataset [23], [44], [45] is collected in traffic scenarios for multi-vehicle tracking. Recently, TAO [36] features 2, 907 HD videos in diverse environments, which is significantly larger, longer, and more diverse than the previous proposed datasets. 2.3

Drone-based Datasets

Besides the aforementioned object detection and tracking datasets, various drone-captured datasets are proposed in recent years for object detection [3], [5], [21], [22], [25], tracking [2], [4], [6], [28], [54], and semantic segmentation [55].

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Fig. 1: Annotated example images in the proposed datasets. The dashed bounding box indicates the object is occluded. Different colors indicate different classes of objects. For better visualization, only a few attributes are displayed. Hsieh et al. [5] is the first aerial dataset for car counting in parking lot scenarios. After that, Xia et al. [21] propose a large-scale dataset in aerial images collected by different sensors and platforms to advance object detection research in earth vision. Barekatain et al. [25] develop the OkutamaAction dataset for concurrent human action detection, including 43 minute-long fully-annotated sequences with 12 action classes. Recently, MOR-UAV [22] proposes a largescale video dataset for the moving object recognition task, i.e., localizing and classifying the moving objects simultaneously in video frames. Meanwhile, the UAV123 dataset [2] is collected for single object tracking, captured by drones at low-altitude aerial perspectives. Li and Yeung [28] collect 70 video sequences of high diversity by drone-equipped cameras for single object tracking evaluation. Robicquet et al. [6] collect several video sequences using drone-equipped cameras in campuses, including various types of objects, (i.e., pedestrians, bikes, skateboarders, cars, buses, and golf carts). Du et al. [4], [54] also construct a UAV benchmark for three tasks, i.e., object detection, single object tracking, and multiple object tracking. Besides, the Semantic Drone dataset5 focuses on semantic understanding of urban scenes from bird view, including 400 images for training and 200 images for testing with the resolution of 6000 × 4000. Similarly, the UAVid dataset [55] is also a UAV dataset for semantic segmentation, including 30 video sequences in slanted views. In contrast to the aforementioned datasets captured in limited scenarios, our VisDrone dataset is collected in various urban scenes, focusing on real world problems with new challenges, e.g., large scale and viewpoint variations, and heavy occlusions.

3

V IS D RONE OVERVIEW

A critical basis for effective algorithm evaluation is a comprehensive dataset. For this purpose, in VisDrone, we systematically collect the largest dataset to advance the object 5. http://dronedataset.icg.tugraz.at/

detection and tracking research on drones to date. It consists of 263 video clips with 179, 264 frames and additional 10, 209 static images. The videos/images are acquired by various drone platforms, i.e., DJI Mavic, Phantom series (3, 3A, 3SE, 3P, 4, 4A, 4P), including different scenarios across 14 different cites in China, i.e., Tianjin, Hongkong, Daqing, Ganzhou, Guangzhou, Jincang, Liuzhou, Nanjing, Shaoxing, Shenyang, Nanyang, Zhangjiakou, Suzhou and Xuzhou. The dataset covers various weather and lighting conditions, representing diverse scenarios in our daily life. The maximal resolutions of video clips and static images are 3840 × 2160 and 2000 × 1500, respectively. The VisDrone benchmark focuses on the following four tasks (see Fig. 1), i.e., DET, VID, SOT and MOT. We construct a website: http://www.aiskyeye.com/ for accessing the VisDrone dataset and perform evaluation of those four tasks. Notably, for each task, the images/videos in the training, validation, and testing subsets are captured at different locations, but share similar scenarios and attributes. The training subset is used to train the algorithms, the validation subset is used to validate the performance of algorithms, the test-challenge subset is used for workshop competition, and the test-dev subset is used as the default test set for public evaluation. We manually annotate the bounding boxes of different categories of objects in each image or frame. After that, crosschecking is conducted to ensure annotation quality. The annotated ground-truths for training and validation subsets are made available to participants, but the groundtruths of the testing subset are reserved in order to avoid (over)fitting of algorithms. To participate our challenge, research teams are required to create their own accounts using email addresses. After registration, participants can choose the tasks of interest, and submit the results specifying locations or trajectories of objects in the images or videos using the corresponding ac-

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counts. The participants are encouraged to use the provided training data, but additional training data is allowable after declaration in submission. In the following subsections, we describe the data statistics and annotation of the datasets for each track in detail.

4

DET T RACK

The DET track tackles the problem of localizing multiple object categories in the image. For each image, algorithms are required to predict the bounding boxes of all the object instances of predefined object categories, with a real-valued confidence. 4.1

Data Collection and Annotation

The DET dataset consists of 10, 209 images in unconstrained challenging scenes, including 6, 471 images in the training subset, 548 in the validation subset, 1, 580 in the test-challenge subset, and 1, 610 in the test-dev subset. We plot the number of objects in different object categories with different occlusion degrees in Fig. 2. Notably, the class imbalance issue significantly affect the detection performance. For example, the number of the awning-tricycle instances is more than 40× less than the car instances. In this track, we mainly focus on people and vehicles in daily life and define ten object categories, including pedestrian, person6 , car, van, bus, truck, motor, bicycle, awningtricycle, and tricycle. Some rarely occurring vehicles are ignored, e.g., machineshop truck, forklift truck, and tanker. We also provide two attributes of each annotated bounding box to analyze the algorithms thoroughly, i.e., the occlusion and truncation ratios. Specifically, occlusion ratio α denotes the fraction of objects being occluded by other objects or background, including no occlusion ($\delta = 0\%$), partial occlusion ($\delta \in (0\%, 50\%]$), and heavy occlusion ($\delta \in (50\%, 100\%]$). Truncation ratio denotes the degree of object parts appearing outside a frame when the object is captured near the frame boundary. It is estimated based on the region outside the frame by human. If the truncation ratio is larger than 50%, the instance is not considered in evaluation. 4.2

Evaluation Protocol

Similar to the metrics in MS COCO [19], the performance of algorithms is evaluated by the average precision (AP) across different object categories and intersection over union (IoU) thresholds. Specifically, AP is computed by averaging over all 10 IoU thresholds, i.e., in the range [0.50 : 0.95] with uniform step size 0.05 of all categories. AP50 and AP75 are computed at the single IoU thresholds 0.5 and 0.75 respectively. Besides, the AR1 , AR10 , AR100 , and AR500 scores are the maximum recalls given 1, 10, 100 and 500 detections per image. Please refer to [19] for more details. 4.3

Review of Image Object Detection Methods

Deep convolutional network dominates the object detection field in recent years, such as Faster R-CNN [56], Mask RCNN [57], Cascade R-CNN [58], YOLOv3 [59], and CenterNet [60]. We briefly summarize some popular detection 6. If a human maintains standing pose or walking, we classify it as pedestrian; otherwise, it is classified as a person.

methods used in the submissions of the VisDrone workshops, which are roughly grouped into two categories, i.e., anchor-based methods and anchor-free methods. In addition, we also introduce some representative object detection methods for beginners to get started in this domain. Anchor-based methods predict a bounding box location and a category label for each instance in an image relying on anchor boxes7 . It can divided into two categories, i.e., the two-stage approach, including [56], [58], [61], and the one-stage approach, including [59], [62], [63], [64]. The twostage approach generally consists of two modules. The first module is designed to generate a sparse set of object proposals and the second module is used to predict the accurate object regions and the corresponding category labels. The representative two-stage methods are described as follows.

- Faster R-CNN [56] is formed by the region proposal network (RPN) to first select the candidate bounding boxes of objects and Fast R-CNN [65] to further generate the accurate object regions and class labels.
- FPN [61] uses feature pyramids to build multi-scale feature maps to improve the detection accuracy.
- Light-RCNN [66] relies on the thin base feature map and cheap R-CNN subnet formed by a pooling and fully-connected layers to construct high efficient detector heads.
- Cascade R-CNN [58] designs the cascade architecture with a sequence of detection heads trained with the increasing IoU thresholds, to be sequentially more selective against close false positives. In contrast to the two-stage approach, the one-stage approach directly predicts objects by sampling over regular and dense

locations, scales and aspect ratios, instead of using the time-consuming region proposal generation module. The representative methods are presented as follows.

- YOLOv3 [59] is improved from YOLO9000 [67] by making a bunch of design changes, such as designing the predictions across scales and using the feature extractor Darknet-53. After that, several YOLO successors [68], [69] further improve the detection accuracy using a bag of tricks.
- SSD [62] directly predicts the locations and scales of objects in different scales of feature maps based on a set of preset anchor boxes.
- RetinaNet [63] designs the focal loss to address the class imbalance issue by reshaping the standard cross entropy loss, i.e., down-weights the loss assigned to the well-classified examples.
- RefineDet [64] uses the anchor refinement module to filter out negative anchors and coarsely adjust positive anchors. Then the object detection module is introduced to take the refined anchors as the input to further regress object locations and sizes and predict multiclass labels. It performs better than the two-stage methods and maintains comparable efficiency of one-stage methods. Anchor-free methods rely on points to predict the objects instead of anchor boxes, such as corner points, center 7. Anchor boxes are a set of predefined bounding boxes with various scales and aspect ratios, which are used for predicting the locations and sizes of object instances.

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Fig. 2: The number of objects with different occlusion degrees of different object categories in the subsets of the DET track. points, and keypoints, which solves the two limitations of the anchor-based methods, i.e., (1) the hand-crafted anchor boxes with predefined scales and aspect ratios are sensitive to specific dataset, and (2) densely placed anchor boxes bring huge computational cost and memory requirements. There are two anchor-free methods widely used in the challenges. That is, Duan et al. [70] design the CornerNet, which use the center, the top-left corner and the bottom-right corner of bounding boxes to detect each object as a triplet, improving both precision and recall. Another method is CenterNet [60], which models the object as a single point, i.e., the center point of its bounding box, and regresses other properties, such as object size, dimension, orientation, and pose, directly from image features at the center location. Meanwhile, FSAF [71] attaches the anchor-free branch to each level of the feature pyramid based on anchorbased detectors [63], allowing box encoding and decoding in the anchor-free manner at an arbitrary level. FCOS [72] attempts to avoid all computational cost and hyperparameters regarding to anchor boxes and solves the object detection in the per-pixel prediction fashion, with low complexity. RepPoints [73] represents objects as a set of sample points critical for both localization and recognition. After that, RepPoints v2 [74] enhances the original regressionbased RepPoints by integrating the verification task for better performance. Other strategies. Besides, there are several other strategies designed to further improve the object detection accuracy.

- Ensemble learning combines the predictions of multiple aforementioned models (e.g., Faster R-CNN [56], Cascade R-CNN [58], YOLOv3 [59]) to reduce the variance of predictions and improve the performance. Besides, fusing different backbone networks8 is another alternative. For example, CBNet [75] assembles multiple identical backbones to construct a more powerful backbone by composite connections between the adjacent backbones.
- Feature extraction. Appearance plays a critical role in object detection. Researchers rack their brains to design different networks to exploit discriminative features to improve the performance. Inspired by FPN [61], Libra R-CNN [76] strengthens multi-level features using the same deeply integrated balanced semantic features. HRNet [77] connects the convolution layers from high to low resolutions in parallel to generate 8. The backbone network denotes the feature extracting network, which is used to extract the features of the input images or videos.

discriminative high-resolution representations. DetNet [78] introduces extra stages into traditional backbone networks, while maintains high spatial resolution in deeper layers. DetectoRS [79] develops recursive feature pyramid at macro levels to exploit extra feedback connections from FPN into the bottom-up backbone layers, and switchable atrous convolution at micro levels to convolve the features with different atrous rates. Notably, other effective modules are also introduced to further enhance the feature representations, such as spatial

group-wise enhance [80], global context [81], deformable convolution [82], squeeze-and-excitation [83], and CARAFE [84].

- Anchor box is important for the anchor-based object detectors. Guided anchor [85] predicts the locations and shapes of anchor boxes by leveraging semantic features to guide the anchor box design. ATSS [86] and PAA [87] automatically select positive and negative anchor box samples according to the statistical characteristics of objects and the probability distributions of anchors respectively.
- Multi-scale training is an effective way to improve the detection accuracy. To accelerate multi-scale training, SNIPER [88] samples chips from multiple scales of the image pyramid in the training stage, conditioned on the image content. Since the detector is trained with the clips of 512 × 512 dimensions, it can reap the benefits of a large batch size and be trained with the batch normalization layers on a single GPU. Meanwhile, YOLOv4 [68] develops the Mosaic data augmentation to mix 4 training images and allows detection of objects outside their normal context, which significantly reduces the need of large mini-batch size.
- Segmentation branch provides more accurate feature representations with strong semantic cue for object detection. Several methods such as Mask R-CNN [57], DeepLab [89] and DES [90] introduce the segmentation branch to predict the masks in parallel with the localizations and sizes of objects to improve the accuracy.
- Region search strategy demonstrates promising results in handling objects with small scales. To improve performance in cluster regions, several approaches such as ClusDet [91] and AutoFocus [92] propose to segment the local regions for better detection of small objects. 4.4

Results and Analysis

Results on the test-challenge set. Top 10 object detec-

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TABLE 2: Comparison results (i.e., percentage of AP scores) of the algorithms on the VisDrone-DET dataset. Method

Representative Model AP AP50 AP75 AR1 AR10 AR100 AR500 VisDrone-2018 challenge: HAL-Retina-Net RetinaNet [63] 31.88 46.18 32.12 0.97 7.50 34.43 90.63 DPNet Faster R-CNN [56] 30.92 54.62 31.17 1.05 8.00 36.80 50.48 DE-FPN FPN [61] 27.10 48.72 26.58 0.90 6.97 33.58 40.57 CFE-SSDv2 SSD [62] 26.48 47.30 26.08 1.16 8.76 33.85 38.94 RD4 MS RefineDet [64] 22.68 44.85 20.24 1.55 7.45 29.63 38.59 L-H RCNN+ Light-RCNN [66] 21.34 40.28 20.42 1.08 7.81 28.56 35.41 Faster R-CNN2 Faster R-CNN [56] 21.34 40.18 20.31 1.36 7.47 28.86 37.97 RefineDet+ RefineDet [64] 21.07 40.98 19.65 0.78 6.87 28.25 35.58 DDFPN FPN [61] 21.05 42.39 18.70 0.60 5.67 28.73 36.41 YOLOv3 DP YOLOv3 [59] 20.03 44.09 15.77 0.72 6.18 26.53 33.27 VisDrone-2019 challenge: DPNet-ensemble Cascade R-CNN [58] 29.62 54.00 28.70 0.58 3.69 17.10 42.37 RRNet Zhou et al.'s CenterNet [60] 29.13 55.82 27.23 1.02 8.50 35.19 46.05 ACM-OD FPN [61] 29.13 54.07 27.38 0.32 1.48 9.46 44.53 S+D Cascade R-CNN [58] 28.59 50.97 28.29 0.50 3.38 15.95 42.72 BetterFPN FPN [61] 28.55 53.63 26.68 0.86 7.56 33.81 44.02 HRDet+ HRDet [77] 28.39 54.53 26.06 0.11 0.94 12.95 43.34 CN-DhVaSa Zhou et al.'s CenterNet [60] 27.83 50.73 26.77 0.00 0.18 7.78 46.81 SGE-cascade R-CNN Cascade R-CNN [58] 27.33 49.56 26.55 0.48 3.19 11.01 45.23 EHR-RetinaNet RetinaNet [63] 26.46 48.34 25.38 0.87 7.87 32.06 38.42 CNAnet Cascade R-CNN [58] 26.35 47.98 25.45 0.94 7.69 32.98 42.28 VisDrone-2020 challenge: DroneEye2020 Cascade R-CNN [58] 34.57 58.21 35.74 0.28 1.92 6.93 52.37 TAUN ATSS [86] 34.54 59.42 34.97 0.14 0.72 12.81 49.80 CDNet Cascade R-CNN [58] 34.19 57.52 35.13 0.80 8.12 39.39 52.62 CascadeAdapt Cascade R-CNN [58] 34.16 58.42 34.50 0.84 8.17 39.96 47.86 HR-Cascade++ Cascade R-CNN [58] 32.47 55.06 33.34 0.94 7.81 37.93 50.65 MSC-CenterNet Zhou et al.'s CenterNet [60] 31.13 54.13 31.41 0.27 1.85 6.12 50.48 CenterNet+ Zhou et al.'s CenterNet [60] 30.94 52.82 31.13 0.27 1.84 5.67 50.93 ASNet ATSS [86] 29.57 52.25 29.37 0.25 1.69 6.46 46.01 CN-FaDhSa Zhou et al.'s CenterNet [60] 28.52 49.50 28.86 0.26 1.76 6.32 48.06 HRNet Duan et al.'s CenterNet [70] 27.39 49.90 26.71 0.80 7.67 33.67 46.16 VisDrone-dev: CornerNet [93] 23.43 41.18 25.02 0.45 4.24 33.05 34.23 Light-RCNN [66] 22.08 39.56 23.24 0.32 3.63 31.19 32.06 FPN [61] 22.06 39.57 22.50 0.29 3.50 30.64 31.61 Cascade R-CNN [58] 21.80 37.84 22.56 0.28 3.55 29.15 30.09 DetNet [78] 20.07 37.54 21.26 0.26 2.84 29.06 30.45 RefineDet [64] 19.89 37.27 20.18 0.24 2.76 28.82 29.41 RetinaNet [63] 18.94 31.67 20.25 0.14 0.68 7.31 27.59

tors in the VisDrone-DET2018 [7], VisDrone-DET2019 [10] and VisDrone-DET2020 [14] challenges are presented in Table 2. In contrast to existing object detection datasets, e.g., MS COCO [19] and UA-DETRAC [23], one of the

most challenging issues in the VisDrone-DET dataset is the extremely small scale of objects. As shown in Table 2, we find that HAL-Retina-Net and DPNet are the only two methods achieving higher than 30% AP in the VisDrone-DET2018 challenge [7]. Specifically, HAL-Retina-Net uses the squeeze-and-excitation [83] and downsampling-upsampling [94] modules to learn both the channel and spatial attentions9 on multi-scale features. To detect small scale objects, it removes higher convolutional layers in the feature pyramid. The second best detector DPNet uses FPN [61] to extract multi-scale features and uses ensemble mechanism to combine three detectors with different backbones, i.e., ResNet-50, ResNet-101 and ResNeXt. Following DPNet, DE-FPN and CFE-SSDv2 also employ multi-scale features to achieve good performance. RD4 MS trains 4 variants of RefineDet [64], i.e., three use SEResNeXt50 and one uses ResNet-50 as the backbone network. Moreover, DDFPN introduces deep back-projection superresolution network [95] to upsample the image using the deformable FPN architecture [82]. Notably, most of the submitted methods use multi-scale testing strategy to improve detection performance effectively. In the VisDrone-DET2019 challenge [10], DPNetensemble achieves the best results with 29.62% AP score. It uses the global context module [81] to integrate context information and deformable convolution [82] to enhance the transformation modeling capability of the detector. RRNet 9. Inspired by human visual system, attention mechanism can guide the network to grasp important contents within different channels or spatial regions of the feature maps corresponding to images/ videos.

and ACM-OD tie for the second place in ranking with 29.13% AP score. RRNet is improved from [60] by integrating a re-regression module, formed by the ROIAlign module [57] and several convolution layers. ACM-OD introduces an active learning strategy, which is conducted with data augmentation for better performance. Compared with VisDrone-DET2018 challenge [7], the submissions in VisDrone-DET2019 challenge [10] fail to find other effective strategies to further improve the performance. In the VisDrone-DET2020 challenge [14], the use of the Cascade R-CNN [58] framework has become wide-spread due to its high performance and easy extensibility. Compared with the baseline Cascade R-CNN [58] with the mAP score of 16.09%, the submitted varaints largely improve the performance by combining several effective modules. DroneEye2020 is mainly based on Cascade R-CNN [58] with recursive feature pyramid and switchable strous convolution [79], achieving the best performance with 34.57 mAP. TAUN uses mean teacher [96] to train the cascade DetectoRS model [58], [79], which performs similarly as DroneEye2020. CDNet and CascadeAdapt combine Cascade R-CNN [58] with deformable convolutions, and then improve the detection accuracy using several data augmentation strategies such as sub-image splitting and mosaic [68]. These results indicate that the detection accuracy of small objects can be improved by enhancing IoU thresholds to train multiple localization branches. Results on the test-dev set. For the test-dev set, CornerNet [93] achieves the top AP score of 23.43%, which uses the Hourglass-104 backbone for feature extraction. In contrast to FPN [61] and RetinaNet [64] with extra stages against the image classification task to handle objects with various scales, DetNet [78] re-designs the backbone network for object detection, which maintains the spatial resolution and enlarges the receptive field, achieving 20.07% AP score. Meanwhile, RefineDet [64] with the VGG-16 backbone performs better than RetinaNet [63] with the ResNet-101 backbone, i.e., 19.89% vs. 18.94% in terms of AP score. This is because RefineDet [64] uses the object detection module to regress the locations and sizes of objects based on the coarsely adjusted anchors from the anchor refinement module. 4.5

Discussion

To describe the appearance of small objects, top performers share some effective feature extraction modules such as feature pyramid [61], attention mechanism [94] and dilated convolution [79]. In this way, the salient semantic features can be extracted with the larger receptive field. Besides, the ensemble mechanism or cascade architecture of models [58] can further improve the performance in complex scenarios. Although the best detector DroneEye2020 sets the new state-of-the-art in 2020, the best AP score is still less than 35%. Notably, it still performs not well of the small-scale objects, e.g., producing less than 25% mAP score in terms of person and bicycle, demonstrating that the community is badly in need of developing robust methods for real-world applications. There are mainly two issues worth to explore in drone captured visual data. Annotation and evaluation protocol. As shown in Fig. 3, there are groups of objects heavily occluded in drone

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Fig. 4: The number of object trajectories in different categories in the subsets of the VID and MOT tracks. Fig. 3: Descriptions of the challenging issues in the image object detection task. 5.1 captured visual data (see the

orange bounding boxes of bicycles). If we use Non-maximum Suppression (NMS) to suppress duplicate detections in detectors, the majority of true positive objects will be inevitably removed. In some real applications, it is unnecessary and impractical to locate each individual object in the crowd. Thus, it is more reasonable to use a large bounding box with a count number to represent the group of objects in the same category (see the white bounding box of bicycle). Meanwhile, if we use the new annotation remedy, we need to redesign the metric to evaluate detection algorithms, i.e., both the localization and counting accuracy should be considered in evaluation [97]. Coarse segmentation. Current object detection methods use bounding boxes to indicate object instances, i.e., a 4tuple (x, y, w, h), where x and y are the coordinate of the bounding box's top-left corner, and w and h are the width and height of the bounding box. As shown in Fig. 3, it is difficult to predict the accurate location and size of the pedestrian (see the yellow bounding box) due to occlusion and non-rigid deformation of human body. A possible way to mitigate such issue is to integrate coarse segmentation into object detection, which might be effective to remove the disturbance of background area enclosed in the bounding box of non-rigid objects, e.g., person and bicycle, see Fig. 3. In summary, this interesting problem is still far from being solved and worth to explore.

5

VID T RACK

The VID track aims to locate object instances from a predefined set of categories in the video sequences. That is, given a series of video clips, the algorithms are required to produce a set of bounding boxes of each object instance in each video frame (if any), with real-valued confidences. In contrast to DET track focusing on object detection in individual images, we deal with detecting object instances in video clips, which involve temporal consistency in consecutive frames. Five categories of objects are considered in this track, i.e., pedestrian, car, van, bus, and truck. We use the same metrics in the DET track to evaluate the video object detection algorithms.

Data Collection and Annotation

We provide 96 challenging video clips in the VID track, including 56 clips for training (24, 198 frames in total), 7 for validation (2, 846 frames in total), 16 for challenge testing (6, 322 frames in total) and 17 for dev testing (6, 635 frames in total). We plot the number of objects of different object categories in Fig. 4. It is worth mentioning that the class imbalance issue is extremely severe in our dataset, challenging the performance of algorithms. For example, in the training set, the number of car trajectories is more than 50× of the number of bus trajectories. Meanwhile, the length of object trajectories varies dramatically, e.g., the maximal and minimal lengths of object trajectories are 1 and 1, 255, requiring the tracking algorithms to perform well in both the short-term and long-term tracking scenarios. Similar to the DET track, we also provide the annotations of occlusion and truncation ratios of each object and ignored regions in each video frame. 5.2

Review of Video Object Detection Methods

Among all submissions in the challenges, the majority of them are directly derived from the image detectors such as SSD [62], Cascade R-CNN [58], FCOS [72], CenterNet [60], and RetinaNet [63], and integrate the temporal coherence of video sequences to handle appearance deterioration such as motion blur, video defocus of objects. Data association is an effective way to exploit temporal consistency of detections in consecutive frames. A simple solution is to combine image detectors and multiple single object trackers (e.g., ECO [98] and SiamRPN++ [99]) for video object detection. Several submissions in the VisDrone challenges adopt this strategy to improve the accuracy, such as EODST in the VisDrone-VDT2018 challenge [9] and EODST+ in the VID2019 [12] challenge. Moreover, some other methods extend object detections in individual frames into tracks or tubelets. The representative methods are presented as follows.

- T-CNN [100] uses optical flow to propagate the detected bounding box across frames and links the bounding box into tubelets with tracking algorithms.
- Seq-NMS [101] re-scores all detected bounding boxes within a video sequence to search the optimal box linkage.

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- D&T [102] is an end-to-end trained CNN to simulta-neously solve detection and tracking without box-level post-processing, which uses a multi-task loss for framelevel object detection and cross-frame track regression in training. However, long time partial or full occlusion, severe camera view changes, and fast

motion are significant challenging factors in drone-captured videos, making data association based approach less effective. Feature aggregation fuses object features in multiple video frames to improve performance for video object detection. The representative methods as summarized as follows.

- FGFA+ in the VisDrone-VDT2018 challenge [9], [103] leverages optical flow based temporal coherence to aggregate feature maps of nearby frames.
- DFF [104] adopts in-network fine-tuned optical flow to propagate and align the features of selected keyframes to nearby non-keyframes, thus reducing redundant calculation and speeding up the system.
- MANet [105] combines instance and pixel-level feature calibration and aggregation through a motion pattern reasoning module.
- MEGA [106] extracts keyframes to get access to more content using the long range memory module, and enhance their features with both global and local semantic information. However, most of the aforementioned methods combine features of just a few consecutive frames, which are less effective to describe the long-term dynamics of objects. Recurrent neural networks (RNNs) leverage rich temporal information to capture long-range temporal context information in videos.
- a LSTM [107] regresses object locations and categories directly, which uses the association features to represent detected objects. The feature representations are optimized by minimizing the association error.
- STMM [108] serves as the recurrent computation unit to model long-term temporal appearance and motion dynamics, where the spatial-temporal memory is aligned from frame to frame.
- OGEMN [109] is an object guided external memory network with write and read operations to efficiently store and accurately propagate multi-level features. Notably, RNNs suffer from the vanishing gradient problem. It is doubtful that the aforementioned methods can deal with complex scenes in the drone-captured videos that demand the long-range temporal context to help generate accurate results. 5.3

Results and Analysis

Results on the test-challenge set. We report the evaluation results of the submissions in the VisDrone-VDT2018 [9] and VisDrone-VID2019 [12] challenges in Table 3. All the submitted methods focus on dealing with degenerated object appearances in videos by enhancing features or exploiting temporal coherence. In the VisDrone-VDT2018 challenge [9], CFE-SSDv2 produces the best AP score of 21.57%, which is improved from SSD [62] by integrating a feature enhancement module for accurate results. Different from CFE-SSDv2, EODST

TABLE 3: Comparison results (i.e., percentage of AP scores) of the algorithms on the VisDrone-VID dataset. Method CFE-SSDv2 EODST FGFA+ RD CERTH-ODV RetinaNet s DBAI-Det AFSRNet HRDet+ VCL-CRCNN CN-DhVaSa DetKITSY EODST++ Libra-HBR Sniper+ FRFPN FGFA [103] D&T [102] FPN [61] CenterNet [60] CornerNet [93] Faster R-CNN [56]

Representative Model AP AP50 AP75 VisDrone-2018 challenge: SSD [62] 21.57 44.75 17.95 SSD [62] 16.54 38.06 12.03 FGFA [103] 16.00 34.82 12.65 RefineDet [64] 14.95 35.25 10.11 Faster R-CNN [56] 9.10 20.35 7.12 RetinaNet [63] 8.63 21.83 4.98 VisDrone-2019 challenge: Cascade R-CNN [58] 29.22 58.00 25.34 RetinaNet [63] 24.77 52.52 19.38 HRNet [77] 23.03 51.79 16.83 Cascade R-CNN [58] 21.61 43.88 18.32 Zhou et al.'s CenterNet [60] 21.58 48.09 16.76 Cascade R-CNN [58] 20.43 46.33 14.82 SSD [62], FCOS [72] 18.73 44.38 12.68 Libra R-CNN [76] 18.29 44.92 11.64 Faster R-CNN [56] 18.16 38.56 14.79 Faster R-CNN [56] 16.50 40.15 11.39 VisDrone-dev: 14.44 33.34 11.85 14.21 32.28 10.39 12.93 29.88 10.12 12.35 28.93 9.92 12.29 28.37 9.48 10.25 26.83 6.70

AR1

AR10

AR100

AR500

11.85 10.37 9.63 9.67 7.02 5.80

30.46 22.02 19.54 24.60 13.51 12.91

41.89 25.52 22.37 29.72 14.36 15.15

44.82 25.53 22.37 29.91 14.36 15.15

14.30 12.33 4.75 10.42 12.04 8.64 9.67 10.69 9.98 9.72

35.58 33.14 20.49 25.94 29.60 25.80 22.84 26.68 27.18 22.55

50.75 45.14 38.99 33.45 39.63 33.40 27.62 35.83 38.21 28.40

53.67 45.69 40.37 33.45 40.42 33.40 27.62 36.57 39.08 28.40

7.29 7.59 7.03 6.41 6.07 5.93

21.37 19.39 19.71 18.93 18.60 12.98

27.09 26.57 25.59 24.87 24.03 13.55

27.21 25.64 25.59 24.87 24.03 13.55

exploits temporal information to associate object detections in individual frames using the ECO tracking method [98], achieving the second best AP score of 16.54%. The third best FGFA+ is a variant of video object detection method FGFA [103] by using several different data augmentation strategies. Researchers propose several powerful methods improved from the state-of-the-art detectors, such as HRDet [77], Cascade R-CNN [58], CenterNet [60], RetinaNet [63], in the VisDrone-VID2019 challenge [12]. Notably, all top 5 detectors, i.e., DBAI-Det, AFSRNet, HRDet+, VCL-CRCNN and CN-DhVaSa, surpass the top detector CFE-SSDv2 in the VisDrone-VDT2018 challenge [9]. DBAI-Det achieves the best results with 29.22% AP, which integrates the deformable convolution [82] and global context [81] in Cascade R-CNN [58]. AFSRNet ranks the second place with 24.77% AP. It integrates the feature selected anchor-free head [71] into RetinaNet [63]. HRDet+, VCL-CRCNN and CN-DhVaSa are improved from HRDet [77], Cascade RCNN [58], and CenterNet [60], respectively. To deal with the large-scale variations of objects, some detectors, such as DetKITSY and EODST++, employ multi-scale features for detection, which performs better than the state-of-the-art detector FGFA [103]. Notably, most of the aforementioned methods are computationally expensive for practical applications, i.e., the running speeds are less than 10 fps on a workstation with one GTX 1080Ti GPU. Results on the test-dev set. The evaluation results of 2 state-of-the-art video object detection methods [102], [103], and 4 state-of-the-art image object detection methods [56], [60], [61], [93] on the test-dev set are reported in Table 3. We find that the two video object detectors performs much better than the four image object detectors. For example, the second best video object detector D&T [102] improves 1.28% AP score compared to the top image object detector FPN [61], which demonstrates the importance of exploiting the temporal information in video object detection. 5.4

Discussion

In contrast to the DET task, VID methods suffers from the degenerated object appearances challenge in videos such as motion blur, pose variations, and video defocus.

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Exploiting temporal coherence and aggregating features in consecutive frames are two effective ways to handle such challenges. However, we observe that the majority of submitted methods rely on image based object detectors, resulting in inferior detection performance. A few submissions with additional tracking module are not matured in modeling temporal consistency of objects in consecutive frames. Notably, all the submitted methods produce less than 15% mAP score on the person and bicycle categories. In summary, the way to exploit temporal information is still an open question for VID. Temporal coherence. A feasible way to exploit temporal coherence is integrating object trackers, e.g., ECO [98] and SiamRPN++ [99], into object detection methods. For example, a tracker could be assigned to each detected object instance in individual frames to guide object detection in the following frames, which is effective to suppress false negatives of detectors. Meanwhile, integrating re-identification module into the detectors is another promising way to exploit temporal coherence, as described in D&T [102]. Feature aggregation. Aggregating features in consecutive frames is also a useful strategy to improve accuracy. As stated in FGFA [103], aggregating features of nearby frames along the motion paths to leverage temporal coherence significantly improves the performance. Thus, we can take several consecutive frames as input, and feed them into deep neural networks to extract temporal salient features using 3D convolution operations or optical flow methods.

6

SOT T RACK

For the SOT track, we focus on generic single object tracking, also known as model-free tracking [26]. In particular, for an input video sequence and the initial bounding box of the target object in the first frame, the SOT track requires the algorithms to locate the target bounding boxes in the subsequent video frames. 6.1

Data Collection and Annotation

In 2018, we provide 167 video sequences with 139, 276 fully annotated frames, split into four subsets, i.e., the training set (86 sequences with 69, 941 frames in total), validation set (11 sequences with 7, 046 frames in total), test-challenge 2018 set (35 sequences with 29, 367 frames in total), and test-dev set (35 sequences with 32, 922 frames in total). To thoroughly evaluate the performance of algorithms in long-term tracking, we add 25 new collected sequences with 82, 644 frames in total in the test-challenge 2018 set to form the test-challenge 2019 set. The tracking targets in all these sequences include pedestrian, cars, and animals. The statistics of target objects, i.e., the aspect ratio in different frames, the area change ratio, and the sequence length are presented in Fig. 5. The enclosing bounding box of target object in each video frame is annotated to evaluate the performance of trackers. To thoroughly analyze the tracking performance, we also annotate 12 sequence attributes following [2], i.e., aspect ratio change, background clutter, camera motion, fast motion, full occlusion, illumination variation, low resolution, out-of-view, partial occlusion, scale variation, similar object, and viewpoint change. Please refer to [2] for more details.

6.2

Evaluation Protocol

Following [26], we use the success and precision scores to evaluate trackers. Specifically, we plot the success curve, i.e., the percentage of successfully tracked frames vs. bounding box overlap threshold in the range [0, 1]. The success score is computed based on the area under the success plot, which is the primary metric for ranking trackers. The precision score denotes the percentage of frames such that the Euclidean distance between predicted locations and ground-truth locations are within 20 pixels in the image plane. Please refer to [26] for more details. 6.3

Review of Single Object Tracking Methods

Although significant progress has been made in visual tracking, it is still difficult for the state-of-the-art trackers to produce accurate results on the drone-captured videos, due to several challenging factors such as abrupt camera motion and small scales of targets. We roughly divide them into three categories, i.e., the correlation filters based methods, the Siamese network based methods, and the convolutional network based methods. We also highlight several effective SOT methods in the challenges. Correlation filters. Correlation filter is one of the most popular methods in single object tracking, which produces correlation peaks for each interested target in the scene and low responses to background. It is usually implemented by using Discrete Fourier Transform, significantly reducing the storage and computational cost by several orders of magnitude. Several submissions in the VisDrone-SOT2018 challenge [8] are constructed on correlation filters, such as STALE-SRCA, DCST, LZZ-ECO, SDRCO and CFCNN. Meanwhile, we briefly review several correlation filters based methods in literature.

- Staple [110] combines two image patch representations and constructs a model that is inherently robust to both color changes and deformations. After that, Staple CA [111] designs a framework that takes global context into account and incorporates it into the correlation filter trackers to boost the performance while maintaining the high frame rate.
- ECO [98] improves the discrete correlation filter in three aspects, i.e., a factorized convolution operator for parameter reduction, a generative model for better sample diversity and training efficiency, and a conservative model update strategy for robustness.
- C-COT [112] presents an implicit interpolation model to train multi-resolution continuous convolution filters. Meanwhile, CFWCR [113] redesigns the final confidence score function by adding the weighted sum operation, showing improvements compared to ECO [98].
- BACF [114] designs a background-aware correlation filter that efficiently models the variations of both foreground and background. Siamese network. Besides the correlation filters, Siamese network is another popular method in the single-object tracking field with promising performance, which learns the

representations of targets by minimizing the similarities of targets in consecutive frames. The representative methods include SiameseFC [115], DSiam [116], and SiamRPN++

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Fig. 5: (a) The number of frames vs. the aspect ratio (height divided by width) change rate with respect to the first frame, (b) the number of frames vs. the area variation rate with respect to the first frame, and (c) the distributions of the number of frames of video clips, in the subsets for the SOT track. [99]. In the VisDrone-SOT2019 challenge [11], 5 trackers use the Siamese network architecture, i.e., DC-Siam, DR-V-LT, SiamDW-FC, SiamFCOT and SiamRPN++. [115] constructs a fully-convolutional Siamese network, which is offline trained to locate an exemplar image within the search region.

- DSiam [116] is a dynamic Siamese network, which uses a fast transformation learning model to enable effective online learning of target appearance variation and background suppression from previous frames.
- SiamRPN++ [99] designs a spatial-aware sampling strategy to train a ResNet-driven Siamese tracker with significant performance gain.
- SiamMask [117] improves the offline training procedure of the fully-convolutional Siamese approaches by augmenting their loss with a binary segmentation task, i.e., producing class-agnostic object segmentation masks and rotated bounding boxes.
- Siam R-CNN [118] presents a Faster R-CNN [56] based re-detection architecture for long-term object tracking. It designs a tracklet-based dynamic programming algorithm to take advantage of re-detections of both the first-frame template and the predictions of previous frames.
- SiameseFC

CNNs. Some other researchers design various CNN architectures for SOT, such as MDNet [119], VITAL [120], CFNet [121], TRACA [122], ATOM [123], and DiMP [124]. The top performers in the challenges are improved from the aforementioned trackers, such as C3DT, DeCom, BTT, VITALD in VisDrone-SOT2018 [8], ACNT, ATOMFR, ED-ATOM, SMILE and TIOM in VisDroneSOT2019 [11], and SMILEv2, LTNMI, ECMMAR, CVPsuperdimp, DIMP+SiamRPN, DiMP AR and DiMP-101 in VisDrone-SOT2020 [16].

- MDNet [119] uses some shared layers and multiple

branches of domain-specific layers to construct the network, where the domains correspond to individual training sequences and each branch is responsible for binary classification to identify target in each domain.

- VITAL [120] identifies the mask of target that maintains the most robust features over a long temporal span using the adversarial learning.
- CFNet [121] is the first attempt to interpret the correlation filter learner as a differentiable layer in a closedform, which enables learning deep features to be tightly

coupled to the correlation filter.

- TRACA [122] develops a context-aware correlation filter based tracker using multi-expert auto-encoders. The best expert auto-encoder is selected for the target in the tracking phase.
- ATOM [123] proposes a tracking architecture formed by dedicated target estimation, which aims to predict the overlap between ground-truth box and estimated box.
- DiMP [124] presents a target prediction network, which is derived from a discriminative learning loss by designing a dedicated optimization process for fast convergence. 6.4

Results and Analysis

Results on the test-challenge set. We report the success and precision scores of the top 10 submissions in the VisDrone-SOT2018 [8], VisDrone-SOT2019 [11], and VisDrone-SOT2020 [16] challenges in Fig. 6(a) and (b). As shown in Fig. 6(a), we find that most of the correlation filter based methods do not perform well in VisDrone-SOT2018 [8]. For example, the winner LZZ-ECO, which combines ECO [98] and YOLOv3 [59], only produces 68.0 success score and 92.9 precision score on the test-challenge 2018 set. Thus, in the following VisDrone-SOT2019 challenge [11], researchers shift their focus to the deep neural network based methods. Specifically, ATOMFR

integrates squeeze-and-excitation [83] into the ATOM [123] tracking framework to capture the interdependencies among feature channels and suppress feature channels that are rarely used in the target size and location prediction, achieving the top accuracy on the test-challenge 2018 set with 75.5 success score and 94.7 precision score. Moreover, in VisDrone-SOT2020 [16], researchers combine ATOM [123], SiamRPN++ [99], Siam RCNN [118], and DiMP [124] to construct the LTNMI tracker, which achieves the best results with 76.5 success score and 92.3 precision score on the test-challenge 2018 set. Notably, multiple trackers ranked in top 10 are the variants of DiMP [124] in VisDrone-SOT2020. As shown in Fig. 6(b), we find that the success and precision scores of the trackers in VisDrone-SOT2018 [8] are significantly decreased compared with the trackers in VisDrone-SOT2019 [11], i.e., the best tracker LZZ-ECO in VisDrone-SOT2018 produces 68.0 success score and 92.9

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precision score vs. the best tracker ED-ATOM in VisDroneSOT2019 produces 48.9 success score and 81.9 precision score. This phenomenon demonstrates that the 25 new collected long-term tracking sequences greatly challenge the performance of the state-of-the-art tracker. Meanwhile, compared with VisDrone-SOT2019, we observe significant improvements of tracking accuracy in VisDrone-SOT2020. Specifically, the winner SMILEv2 in VisDrone-SOT2020 achieves 55.5 success score and 91.9 precision score, which surpasses the best tracker ED-ATOM in VisDrone-SOT2019 with a large margin. Meanwhile, among all submissions in the challenges from 2018 to 2020, some trackers attempt to integrate the state-of-the-art detectors to re-detect the target to deal with drifting problem. For example, in VisDrone-SOT2018 [8], LZZ-ECO leverages the detector YOLOv3 [59] to determine the target location if large deformation or camera motion occurs. VITALD trains RefineDet [64] as a reference for the VITAL tracker [120], i.e., providing reliable target candidates for the target and background classification. In VisDrone-SOT2020 [16], DiMP AR activates the Faster RCNN detector [56] to generate target candidates in the video frame if the confidence of tracked target is less than a pre-defined threshold. PrSiamR-CNN is constructed by combining the Siam R-CNN [118] tracker and Faster R-CNN for re-detection. Another critical engine for performance improvements is the utilization of large-scale datasets, such as MS COCO [19], GOT-10k [29], ImageNet DET/VID [18], LaSOT [32], TrackingNet [30], and YoutubeBB [125], in offline training. For example, ED-ATOM achieves the top results in VisDrone-SOT2019 [11], which is offline trained on ImageNet DET/VID [18], MS COCO [19], Got-10k [29], and LaSOT [32]. Specifically, the ED-ATOM tracker is improved from ATOM [123] by using the low-light image enhancement method [126] and the online data augmentation scheme [127]. In addition, the ensemble strategy is also an effective way to improve the performance. In VisDrone-SOT2019 [11], Siam-OM adopts ATOM [123] to handle the short-term tracking, and DaSiam [128] uses ResNet to handle the longterm tracking. SIMLE combines two state-of-the-art trackers ATOM [123] and SiamRPN++ [99], where different features play different roles in tracking process. DR-V-LT integrates the distractor-aware verification network MDNet [119] into SiamRPN++ [99], which is robust to the similar objects challenge. In VisDrone-SOT2020 [16], the top 3 performers combine various tracking methods to handle challenges in different scenarios. SMILEv2 is an ensemble of three recent state-of-the-art trackers, i.e., DiMP [124], SiamMask [117] and SORT [129]. Similar to SMILEv2, LTNMI combines four trackers including ATOM [123], SiamRPN++ [99], Siam R-CNN [118] and DiMP [124]. ECMMR is constructed by ensemble the results of DiMP [124] and SiamRPN++ [99]. DiMP is used to deal with the target disappearing caused by full occlusion or fast perspective conversion and SiamRPN++ is designed to distinguish distractors in clutter background. Results on the test-dev set. In addition, we evaluate 21 state-of-the-art trackers on the test-dev set in Fig. 6(c). ATOM [123] (marked as the orange cross in the top-right

corner) obtains the best 64.5 success score and the third best 83.0 precision score. This is attributed to the network trained offline on large-scale datasets to directly predict the IoU overlap between the target and a bounding box estimate. However, it performs not well in terms of low resolution and out of view. Besides, MDNet [119] and SiamRPN++ [99] obtain top 3 success scores based on large-scale training. In summary, training on large-scale datasets brings significant performance improvement of trackers. 6.5

Discussion

As mentioned above, compared with VisDrone-SOT2019 [11], the tracking accuracy is significantly improved in VisDrone-SOT2020 [16]. Previously, the correlation filters based trackers [98], [110] are the most popular methods. In recent years, the CNN based trackers [123], [124] with online update module quickly dominate this filed. Notably, large-scale training data [18], [19], [29], [30], [32], [125] is crucial for the CNN based trackers.

However, long-term tracking is still challenging for the trackers even though the re-detection module [56], [59], [64] is incorporated. In addition, it still needs extensive efforts to improve the robustness of trackers to the factors, such as abrupt motion, low resolution, and occlusion, to meet the requirements of real-world applications. Abrupt motion. Most of previous SOT methods [99], [117] formulate object tracking as the one-shot detection task, which use the bounding box in the first frame as the only exemplar. These methods rely on the pre-set anchor boxes to regress the bounding box of target in consecutive frames. However, the pre-defined anchor boxes can not adapt to various motion patterns and scales of targets, especially when the fast motion and occlusion occur. To this end, we can integrate the motion information or re-detection module to improve the accuracy of tracking algorithms. Low resolution is another challenging factor that greatly affects tracking accuracy. Most of the existing methods [99], [123] merely focus on the appearance variations of target region, producing unstable and inaccurate results. We believe that exploiting context information surrounding the target can be helpful to improve the tracking performance, especially for the targets with small scales. Occlusion might happen frequently in tracking process, which is the obstacle to produce accurate tracking results. Some previous algorithms [53] attempt to use part-based representations to handle the appearance changes caused by occlusion. Meanwhile, using a re-detection module [130] is another effective strategy to get rid of occlusion, i.e., the re-detection module is able to detect the target after reappearing in the scenes. In addition, predicting the motion patterns of the target based on its trajectory in history is also a promising direction worth to explore.

7

MOT T RACK

The MOT track aims to recover the trajectories of objects in video sequences. In the VisDrone-VDT2018 challenge [9], we divide this track into two sub-tracks depending on whether prior detection results in individual frames are used. In the VisDrone-MOT2019 [13] and VisDrone-MOT2020 [15] challenges, we merge these two tracks, and do not distinguish

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Fig. 6: The success vs. precision scores of (a) the top 10 trackers in VisDrone-SOT2018 (red marks), VisDrone-SOT2019 (blue marks) and VisDrone-SOT2020 (purple marks) on the test-challenge 2018 set, (b) the top 10 trackers in VisDroneSOT2019 (blue marks) and VisDrone-SOT2020 (purple marks) on the test-challenge 2019 set, (c) 21 state-of-the-art trackers on the test-dev set. submitted algorithms according to whether they use object detection in each video frame as input or not. Notably, this track uses the same data as the VID track, namely five categories of objects, i.e., pedestrian, car, van, bus, and truck, in 96 video clips.

7.1

Evaluation Protocol

For MOT without input detections, we use the metrics in [131] to evaluate the performance. Specifically, we sort the predicted tracklets from algorithms based on the average confidence of the detections of the same identity. If the IoU overlap between the tracklet and the corresponding groundtruth is larger than a threshold, we treat it as a correct one. Following [131], we average the mean average precision (mAP) per object class over three different thresholds (i.e., 0.25, 0.50, and 0.75) to rank the algorithms. For MOT with input detections, we use the CLEAR-MOT metrics in [24] for evaluation, i.e., MOTA, MOTP, IDF1, FAF, MT, ML, FP, FN, IDS, and FM. The MOTA metric is the comprehensive metric aggregating three kinds of errors, i.e., FP, FN and IDS. The MOTP metric calculates the average dissimilarity between all true positives and the corresponding ground-truths. The IDF1 metric indicates the ratio of correctly identified detections over the average number of ground truth and computed detections. The FAF metric indicates the average number of false alarms per frame. The FP metric describes the total number of tracker outputs which are the false alarms, and FN is the total number of targets missed by any tracked trajectories in each frame. The IDS metric describes the total number of times that the matched identity of a tracked trajectory changes, while FM is the times that trajectories are disconnected. Both the IDS and FM metrics reflect the accuracy of tracked trajectories. The ML and MT metrics measure the percentage of tracked trajectories less than 20% and more than 80% of the time span based on the ground-truth respectively. More details refer to [24].

7.2

Review of Multi-Object Tracking Methods

MOT is a challenging problem due to various factors, such as unreliable detection, long-term occlusion and fast motion, which is a hot topic in recent years. Directly applying single object trackers (e.g., KCF [132], CFNet [121] and DaSiameseRPN [128]) to track multiple objects is a natural way to solve the multi-object tracking task. However, the computation cost increases along with the number of objects in scenes, which is impractical in real-life applications. In this section, we briefly review some representative MOT methods in the challenges and literature. Tracking-by-detection approach is popular in MOT due to its superior performance, which formulates the tracking task as the data association problem. In this scheme, object candidates are detected in each individual frames by using the offline trained detectors. After that, the detected objects are associated to generate object trajectories using various optimization algorithms (e.g., Hungarian algorithm [129], [133] and max-flow min-cut [134]) based on the appearance or motion informations of objects.

- GOG [134] uses the min-cost flow algorithm to asso-ciate the input detections in video frames. The cost function is computed based on the appearance and motion information to determine the number of trajectories and their birth and death states.
- SORT [133] leverages high-quality detections to use their positions and sizes for both motion estimation and data association. Moreover, Deep SORT [129] combines appearance information to track objects through longterm occlusions with less identity switches.
- IOU [135] uses the intersection-over-union (IOU) to measure the similarities of detections in consecutive frames for MOT.
- MOTDT [136] handles unreliable detection by collecting candidates from both detection and tracking, and design a scoring function based on CNN to get the optimal selection from a considerable amount of candidates in real-time.

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[137] constructs a graph model to take the tracklets as the vertices, which exploits the temporal information and greatly reduces the computational complexity. Afterwards, the clustering operation is performed on the graph to generate object trajectories. Joint tracking and detection approach is a recent trend in the MOT field, which integrates object detection and tracking into a unified framework, such as Tracktor [138] and FairMOT [139]. In that way, the two tasks can help each other for better performance.

- Tracktor [138] uses the bounding box regression of a detector to predict the position of the target in the next frame. In particular, no training or optimization are performed on the tracking data.
- FairMOT [139] consists of two homogeneous branches to predict pixel-wise objectness scores and reidentification features to obtain high levels of detection and tracking accuracy.
- CenterTrack [140] takes two consecutive frames and a heatmap of prior tracklets as input, and outputs current object centers and tracking offsets to their centers in previous frames. Appearance and motion modeling. In recent years, researchers attempt to leverage deep neural networks to learn discriminative appearance [141], [142], [143], [144] and motion features [145], [146], [147], [148], [149] of targets. In VisDrone-VDT2018 [9], VisDrone-MOT2019 [13] and VisDrone-MOT2020 [15], some representative methods of appearance modeling are described as follows.
- Multi-scale representation: The deep affinity network [141] associates the detected objects in multiple consecutive frames. Specifically, the multi-scale features are extracted to describe the objects, and the

identities of detections at different frames are inferred by analyzing the exhaustive permutations of extracted features.

- Onmi-scale representation: The lightweight OSNet [142] extracts omni-scale feature representation by the residual block with multiple convolutional streams. Meanwhile, a unified aggregation gate is designed to dynamically fuse multi-scale features.
- ReID representation: A strong ReID model is proposed in [143] without too much extra consumption. Besides, various training tricks are introduced to improve the performance, including warmup learning, random erasing augmentation, label smoothing, smaller last stride, BNNeck and center loss.
- Multiple granularity representation: The multiple granularity network [144] is a multi-branch deep network architecture formed by one branch for global feature representation and two branches for local feature representations, which integrates discriminative information with various granularities. Besides the appearance information, the motion features are also critical for MOT. Some representative methods are summarized as follows.
- Motion patterns are important low-level cues for MOT, including forward-backward flow [145], KLT10 and optical flow [146], [147].
- TrackletNet
- https://cecas.clemson.edu/~stb/klt/

TABLE 4: Comparisons results of the algorithms on the VisDroneMOT dataset using the evaluation protocol in [131]. Method

AP AP@0.25 AP@0.50 AP@0.75 APcar APbus APtrk APped APvan VisDrone-2018 challenge: Ctrack 16.12 22.40 16.26 9.70 27.74 28.45 8.15 7.95 8.31 deep-sort d2 10.47 17.26 9.40 4.75 29.14 2.38 3.46 7.12 10.25 MAD 7.27 12.72 7.03 2.07 16.23 1.65 2.85 14.16 1.46 VisDrone-2019 challenge: DBAI-Tracker 43.94 57.32 45.18 29.32 55.13 44.97 42.73 31.01 45.85 TrackKITSY 39.19 48.83 39.36 29.37 54.92 29.05 34.19 36.57 41.20 Flow-Tracker 30.87 41.84 31.00 19.77 48.44 26.19 29.50 18.65 31.56 HMTT 28.67 39.05 27.88 19.08 44.35 30.56 18.75 26.49 23.19 TNT DRONE 27.32 35.09 26.92 19.94 38.06 22.65 33.79 12.62 29.46 GGDTRACK 23.09 31.01 22.70 15.55 35.45 28.57 11.90 17.20 22.34 IITD DeepSort 13.88 23.19 12.81 5.64 32.20 8.83 6.61 18.61 3.16 T&D-OF 12.37 17.74 12.94 6.43 23.31 22.02 2.48 9.59 4.44 SCTrack 10.09 14.95 9.41 5.92 18.98 17.86 4.86 5.20 3.58 VCLDAN 7.50 10.75 7.41 4.33 21.63 0.00 4.92 10.94 0.00 VisDrone-2020 challenge: COFE 61.88 64.99 62.00 58.65 79.09 65.26 50.91 56.87 57.26 SOMOT 57.65 70.06 60.13 42.75 68.52 62.10 47.98 54.94 54.69 PAS 50.80 62.24 50.74 39.43 62.59 50.59 42.18 44.34 54.30 Deepsort 42.11 58.82 42.64 24.86 55.06 43.18 41.30 29.10 41.88 YOLO-TRAC 42.10 52.94 41.86 31.49 52.81 48.98 39.17 28.92 40.59 VDCT 35.76 45.86 35.46 25.96 56.94 24.62 28.16 34.00 35.06 CRCNN+IOU 27.23 36.14 28.25 17.31 49.56 16.27 30.18 10.78 29.36 HTC+IOU 26.46 34.39 27.43 17.57 51.18 19.05 21.55 10.77 29.76 HR-GNN 19.54 26.52 19.67 12.42 37.72 15.48 9.98 18.87 15.65 TNT 6.55 10.93 7.00 1.70 1.88 19.51 2.07 1.96 7.32 VisDrone-dev: GOG [134] 5.14 11.02 3.25 1.14 13.70 3.09 1.94 3.08 3.87 IOUT [135] 4.34 8.32 3.29 1.40 10.90 2.15 2.53 1.98 4.11 SORT [129] 3.37 5.78 2.82 1.50 8.30 1.04 2.47 0.95 4.06 MOTDT [136] 1.22 2.43 0.92 0.30 0.36 0.00 0.15 5.08 0.49

TABLE 5: Comparisons results of the algorithms on the VisDroneMOT dataset using the CLEAR-MOT evaluation protocol [24]. Method

MOTA MOTP IDF1 FAF MT ML FP FN IDS FM VisDrone-2018 challenge: TrackCG 42.6 74.1 58.0 0.86 323 395 14722 68060 779 3717 V-IOU 40.2 74.9 56.1 0.76 297 514 11838 74027 265 1380 GOG EOC 36.9 75.8 46.5 0.29 205 589 5445 86399 354 1090 SCTrack 35.8 75.6 45.1 0.39 211 550 7298 85623 798 2042 FRMOT 33.1 73.0 50.8 1.15 254 463 21736 74953 1043 2534 Ctrack 30.8 73.5 51.9 1.95 369 375 36930 62819 1376 2190 VisDrone-dev: GOG [134] 28.7 76.1 36.4 0.78 346 836 17706 144657 1387 2237 IOUT [135] 28.1 74.7 38.9 1.60 467 670 36158 126549 2393 3829 SORT [129] 14.0 73.2 38.0 3.57 506 545 80845 112954 3629 4838 MOTDT [136] -0.8 68.5 21.6 1.97 87 1196 44548 185453 1437 3609

- Motion networks are designed to learn the complex

long-term temporal dependencies of targets, which are more effective than the predefined motion patterns [148], [149]. Milan et al. [148] propose the first end-toend learning approach for online MOT, without any prior knowledge about target dynamics and clutter distributions. Sadeghian et al. [149] leverage LSTM networks to

track the motion and interactions of targets for longer periods, which is suitable for presence of longterm occlusions. 7.3

Results and Analysis

Results on the test-challenge set. We report the evaluation results of top 10 MOT methods in VisDrone-VDT2018 [9], VisDrone-MOT2019 [13] and VisDrone-MOT2020 [15] based on the evaluation protocols [131] and [24] in Table 4 and 5, respectively. In summary, the MOT performance highly relies on three aspects, i.e., input object detection quality, motion models and appearance models. As shown in Table 4, the submissions in VisDroneMOT2019 [13] achieve significant improvement than that in

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VisDrone-VDT2018 [9]. For example, the best DBAI-Tracker in VisDrone-MOT2019 [13] achieves 25% higher AP score than the best tracker Ctrack in VisDrone-VDT2018 [9]. This is partially attributed to the powerful Cascade R-CNN [58] detector, which provides more accurate input detections than Faster R-CNN [56] and RetinaNet [63]. Meanwhile, exploiting motion information is an effective way to improve the performance. In VisDrone-VDT2018 [9], Ctrack achieves the best AP score 16.12% by aggregating the prediction events in grouped targets and stitching the tracks by temporal constraints. In this way, Ctrack can recover the trajectories of occluded targets. Although deep-sort d2 and MAD use more powerful object detectors RetinaNet [63] and YOLOv3 [59], they fail to make full use of the motion patterns within grouped targets, resulting in inferior results. In VisDrone-MOT2019 [13], three out of the top four trackers (DBAI-Tracker, Flow-Tracker, and HMTT) integrate additional temporal modules such as optical flow [146], [147] to complete association, demonstrating the critical role of motion information in the tracking task. In VisDrone-MOT2020 [15], the AP scores of the submitted algorithms are further improved compared with VisDrone-MOT2019 [13]. The top three methods are COFE, SOMOT and PAS. Besides the strong Cascade R-CNN [58] detector and motion modeling, the re-identification model [142], [143], [144] contributes a great deal to the tracking performance. For example, SOMOT achieves better performance by considering both global and local appearance [144], compared to PAS that only relies on global features [143]. Without the re-identification models, Deepsort and YOLO-TRAC produce inferior AP score of 42.1%. It is worth mentioning that the best tracker COFE employs a coarse-category training strategy. Specifically, it first performs multi-object tracking for each coarse category, e.g., fine-grained classes such as “van”, “bus” and “car” are grouped into a coarse category “vehicle”. After that, the fine-grained class labels of targets are voted by the class labels of detections on the trajectories. For example, if the length of target trajectory is 20, including 10 detections classified as “car”, 6 detections classified as “bus”, and 4 detections classified as “van”, the target is voted as the finegrained class “car”. For the sub-track in VisDrone-VDT2018 [9] with input detections generated by Faster R-CNN [56], TrackCG achieves the best MOTA and IDF1 scores. V-IOU produces slightly inferior MOTA and IDF1 scores than TrackCG, but lower IDS score. It associates object detections in consecutive frames based on the spatial intersection-over-union overlap. We speculate that the overlapping measurement is reliable enough for tracking in drone captured videos, which do not contain large displacements of objects in consecutive frames. GOG EOC achieves the best FAF, FP and FM scores, which uses the overlap and context harmony degree to measure the similarities of detections. SCTrack designs the color correlation costs to maintain object identities. However, the color information is not reliable enough, resulting in inferior MOTA score. FRMOT is an online tracker using the Hungarian algorithm to associate detections, producing relative large IDS and FM scores. Results on the test-dev set. Besides, we evaluate 4 multiobject tracking on the test-dev set with the evaluation

protocols [131] and [24], shown in Table 4 and 5, respectively. Notably, FPN [61] is used to generate object detections in individual frames for the sub-track using prior input detections. GOG [134] and IOUT [135] benefit from global information of whole sequences and spatial overlap between frame detections, achieving the best tracking results in terms of both evaluation protocols [131] and [24]. DeepSORT [129] approximates the inter-frame displacements of each object with a linear constant velocity model, which is independent of object categories and camera motion, significantly degrading its performance. MOTDT [136] computes the similarities between objects using appearance model trained on other large-scale person re-identification datasets without fine-tuning, leading to inferior accuracy. 7.4

Discussion

Most of the MOT methods formulate the tracking task as the data association problem, which aims to associate object detections in sequential frames to generate object trajectories. Thus, the accuracy of object detection significantly influence the performance of MOT. Some submitted MOT methods focus on obtaining strong detections [56], [58], [63] and finegrained feature representations [142], [143], [144], which is the key to achieve the state-of-the-art results. However, the two-stage strategy, i.e., detection and association, is suboptimal due to the separation of these two tasks. Intuitively, integrating object detection and tracking into a unified framework is intuitive to improve the performance. First, the end-to-end model has lower computational complexity and higher efficiency. Second, these two tasks can share information to improve the accuracy. In the following, we discuss two potential research directions to further boost the MOT performance. Similarity estimation. For the data association problem, similarity computation between different detections in individual frames is crucial for the tracking performance. The appearance and motion information should be considered in computing the similarities. For example, a Siamese network offline trained on the ImageNet VID dataset [18] can be used to exploit temporal discriminative features of objects. It can be fine-tuned in tracking process to further improve the accuracy. Meanwhile, several low-level and mid-level motion features are also effective and useful for the MOT algorithms, such as KLT and optical flow. Scene understanding is another effective way to improve the MOT performance. For example, based on the scene understanding module, we can infer the enter or exit ports in the scenes as a strong priori for the trackers to distinguish occlusion, termination, or re-appearing of the targets. Meanwhile, the tracker can also suppress false trajectories based on general knowledge, e.g., the vehicles are only driven on the road rather on the building. In summary, this area is worth further studying.

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C ONCLUSION AND F UTURE R ESEARCH

We introduce a new large-scale benchmark, VisDrone, to facilitate the research of object detection and tracking on drone captured imagery. With over 6, 000 worker hours, a

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vast collection of object instances are gathered, annotated, and organized to drive the advancement of object detection and tracking algorithms. Meanwhile, several representative submitted detection and tracking methods are reviewed, where the best submissions in the four tracks are still short for real applications. From both research and application perspectives, this work discusses some under-developed but critical future issues of object detection and tracking on drone captured imagery. It would shed some light into potential future research directions on drone-based object detection and tracking. Relations between object detection and tracking. Early on, object detection is generally used as the first step to generate candidate object proposals, and object tracking algorithms are required to associate the object proposals to recover the trajectories, i.e., the so-called “tracking-bydetection” framework. Specifically, early object detection methods rely on the sliding-window paradigm and design hand-craft features and classifiers on dense image grids to detect objects, such as Adaboost [150], DPM [151], and ACF [152]. Deep convolutional network dominates the detection field in recent years due to its powerful representation capability, including Faster R-CNN [56], Cascade R-CNN [58], YOLOv3 [59], RefineDet [64] and CenterNet [60]. Meanwhile, for object tracking, most of early methods use the tracking-by-detection paradigm, such as Hungarian algorithm [153], min-cost flow [154], and hypergraph optimization [155], which takes object detection results in individual frames as input, and design algorithms to associate object detections in each frame by exploiting temporal information to complete object tracking. Intuitively, tracking systems clearly benefit from accurate object detections, while are effective to help detectors to produce accurate results by exploiting the temporal information. Some researchers attempt to design the end-to-end frameworks [102], [156], [157], [158] based on deep neural networks to solve object detection and tracking jointly. In this way, object detection and tracking can help each other to boost the performance. We believe that the joint detection and tracking are especially important for the dronecaptured videos. Since the scales of objects are extremely tiny in drone-captured videos, heavily relying on appearance information in traditional methods is less effective. Combining detection and tracking in a unified framework to take advantage of the spatio-temporal context information is worth to pursue. Performance evaluation. In various scenarios, different factors have different importance for detection and tracking. For example, in surveillance scenarios, the accuracies of detections and trajectories are of great importance. Thus we should put more weights on the metrics based on id switches, trajectory fragmentations, and false positives. In

autonomous driving scenarios, the false negatives are of more concern than other factors. Building an appropriate evaluation protocol to meet the requirements in different scenarios is an urgent task in object detection and tracking. Effectiveness and efficiency. Effectiveness and efficiency are both important aspects for algorithms in real applications. For example, the computation resources are limited

on drone platform, making it impossible to deploy a large model on such edge devices. In the VisDrone-Challenges from 2018 to 2020, all submissions focus more on accuracy than efficiency. To promote the developments of algorithms for real-world applications, we plan to consider the running efficiency in the evaluation process in the following VisDrone-Challenges. Recently, the automated neural architecture search (AutoNAS) is a hot topic in research field. It is potentially effective to introduce the AutoNAS technologies [159], [160] to search the model architectures by considering both the effectiveness and efficiency for the drone-based applications. Specifically, for different drone platforms, we need to consider the specific computational power and memory request in the architecture searching process, while maintaining the accuracy. This direction is relatively less developed, and we need to put more efforts on it. Unsolved problems. There still exists several challenges in drone-captured video sequences, such as viewpoint change, motion blur, abrupt motion and small objects. Although the submitted object detection and tracking methods produce promising results in the deep learning era, they are still prone to fail in the aforementioned challenges. This is because most of previous object detection and tracking methods are on the rack to exploit the appearance information to improve the performance. Actually, it is extremely difficult to deal with the challenging cases solely relying on appearance information, e.g., detecting blurred/occluded objects in videos, or tracking multiple objects with similar appearance. To that end, a few attempts exploit the motion information to improve the accuracy, such as high-order motion constraints [161], tensor power iterations [162], and dense structure search on hypergraphs [155]. Although these methods are effective in some scenarios, it is still much room for improvements to meet the requirements of the applications on drones. Constructing a reliable motion model to fully exploit the motion information is a promising direction for future research. On the other hand, current submissions handle with small objects by using multi-scale representations [61] and data augmentation strategies [88]. However, it is difficult to learn effective representations of small objects based on the generic ImageNet or MS-COCO datasets, resulting in inferior performance on our dataset. To improve the accuracy of detectors, it is urgent to collect large-scale datasets and benchmarks for small objects. Moreover, anchor-free object detection methods [60], [72] focus on detecting objects by points, which may be another research direction for small object detection.

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J. Farm Sci., 38(4): (407-412) 2025 RESEARCH PAPER

Evaluation of drone technology in paddy ecosystem against key insect pests S. NAVEEN1, ROOPA S. PATIL1, D. N. KAMBREKAR1 AND SHRIPAD KULKARNI2 Department of Entomology,2Department of Plant Pathology, College of Agriculture, Dharwad University of Agricultural Sciences, Dharwad -580 005, India *E -mail: naveens761919@gmail.com (Received: September, 2024 ; Accepted:December, 2025)

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DOI: 10.61475/JFS.2025.v38i4.16 Abstract: This study, conducted at ICAR-Krishi Vigyan Kendra, Malagi farm, Karnataka, during the kharif season of 202324, evaluated the effectiveness of drone spray technology compared to knapsack sprayers in managing key insect pests in paddy specifically the rice leaf folder (Cnaphalocrocis medinalis) and rice ear head bug (Leptocorisa oratorius). The insecticides used were fipronil 5% SC and profenophos 50% EC applied during the vegetative and reproductive phases of the crop. Drone spraying demonstrated superior pest control, with higher reductions in pest damage compared to knapsack sprayers. For leaf folder control, fipronil via drone reduced leaf damage by 66.96 per cent in the first application, while profenophos recorded a 53.74 per cent reduction. Similar trends were observed for the ear head bug. Additionally, drone spraying had a lesser impact on natural enemies, such as spiders, coccinellids dragon and damselflies, compared to knapsack methods. The results highlight the advantages of drone technology in providing precise pesticide application ensuring better pest management reduced ecological impact and improved conservation of beneficial insects making it a promising alternative for sustainable agriculture. Key words: Drone, Knapsack sprayer, Natural enemies, Rice leaf folder, Rice ear head bug

Introduction Rice (Oryza sativa L.), the world's second most consumed cereal crop, is essential for feeding two-thirds of the global population. India, as the second-largest rice producer after China, plays a crucial role in global rice supply (Rai, 2006). However, 52 per cent of global rice production is lost due to biotic agents, with insect pests responsible for 21 per cent of this yield loss. While chemical spraying remains a primary method for pest management, not all spraying techniques are equally effective and efficient in the paddy ecosystem there is a need for innovative spraying method. Dynamic Remotely Operated Navigation Equipment (DRONE) or an Unmanned Aerial Vehicle (UAV), refers to remotely piloted aircraft controlled directly by a human through radio link. The utilization of drones for pesticide spraying provides a significant advantage by replacing labour intensive and hazardous conventional methods, reducing excessive chemical deposition, controlling pests effectively and efficiently and enabling easier application in waterlogged conditions. Material and methods The study, titled "Evaluation of drone technology in paddy ecosystem against key insect pests" was conducted at ICARKrishi Vigyan Kendra, Sirsi, Malagi farm, Uttara Kannada District, Karnataka, during the kharif season of 2023-24, Sirsi. The research focused on evaluating the efficacy of drone spray technology against key paddy pests and its impact on natural enemies. The field was divided into 320 m^2 plots, with a fivemeter buffer zone between treatments. The RNR-15048 variety was sown with 30 x 10 cm spacing. Insecticides Fipronil 5% SC and Profenophos 50% EC were applied using drones and knapsack sprayers during the crops vegetative and reproductive phases. The drone operated at a speed of 2.8 m/s, 2.5 m above

the canopy, with a 3.5 m spray width. The accuracy of the flight height and flight velocity will be controlled by the well-trained operator. Assessment of leaf folder infestation The damaged leaves and total leaves from 10 randomly selected hills were counted in each treatment. The observations were recorded in all the treatments of insecticides both with drone and knapsack sprayer at one day before spraying (DBS), three, seventh and fourteen days after spraying (DAS). The per cent leaf damage was calculated as follows, Per cent damaged leaves =

Number of damaged leaves x 100 Total number of leaves

Assessment of ear head bug Observations on the number of adult and nymphs of ear head bugs were recorded on 10 hills and averaged to express on per hill basis. The observations were recorded in all the treatments of

insecticides both with drone and knapsack sprayer at one day before spraying (DBS), three, seventh and fourteen days after spraying (DAS). Natural enemies The population count for the natural enemies were done simultaneously on the same hills on which insect population were recorded. The common predators such as coccinellids and spiders were collected by hand in the field and visual counts on ten hills and averaged to express per hill basis. Similarly, population of dragonfly and damselfly were collected with ten sweeps and the numbers of adult populations were assessed per square meter area in the same locations.

J. Farm Sci., 38(4): 2025 Result and discussion This study evaluated the effectiveness of drone and knapsack sprayers in managing key insect pests in paddy specifically focusing on the rice leaf folder (Cnaphalocrocis medinalis) and rice ear head bug (Leptocorisa oratorius) and their relative impact on the natural enemies like spiders, coccinellids, dragon and damsel flies. The insecticides used were fipronil 5% SC and profenophos 50% EC. The results demonstrated that while both insecticides were effective in reducing pest damage and relatively lower impact on the natural enemies, the method of application significantly influenced the control levels. Rice leaf folder (Cnaphalocrocis medinalis) Drone applications of fipronil achieved a mean reduction in leaf damage of 66.96 per cent in the first application and 65.96 per cent in the second. In contrast, fipronil applied via knapsack sprayer resulted in lower reductions of 59.14 per cent and 58.72 per cent, respectively. Profenophos applied with a drone recorded damage reductions of 53.74 per cent in the first application and 53.42 per cent in the second, whereas the knapsack application led to reductions of 46.81 per cent and 49.25 per cent (Table 1). The superior performance of drone spraying is attributed to its ability to deliver a more uniform and precise distribution of insecticide, covering large areas quickly and ensuring consistent application. In comparison, the manually operated knapsack sprayer showed inconsistencies in spray coverage (Fig. 1). Similar findings were reported by Qin et al. (2016), who found that UAV spraying achieved a 91.70 per cent control efficiency, 19.30 per cent higher than knapsack sprayers (72.40%). Wei et al. (2020) also observed better pest control with UAVs compared to knapsack sprayers. Nordin et al. (2021) reported that UAVs achieved 84.70 per cent efficacy, while knapsack sprayers had only 69.30 per cent. Sambaiah et al. (2022) found that UAVs reduced leaf folder damage by 91.80 per cent, while knapsack sprayers achieved a 74.50 per cent reduction.

Fipronil, a phenyl pyrazole, disrupts neurotransmission by inhibiting GABA receptors in insects, leading to higher mortality. Profenophos, an organophosphate that inhibits acetylcholinesterase, was less effective, especially against resistant pests. Fipronil's systemic action allowed it to be absorbed by the plant, providing broader control, while profenophos primarily works on contact, limiting its effectiveness against hidden pests. Vinay (2023) reported that fipronil 5% SC achieved a 64.10 per cent reduction in leaf folder damage, compared to 59.49 per cent with profenophos, reinforcing fipronil's superior efficacy. Firake et al. (2010) recorded a 47.36 per cent reduction in leaf folder damage with fipronil 5% SC, and Vinoth (2014) noted over 95 per cent reduction in damage with fipronil applied at 50 g a.i./ha. Hurali et al. (2020) found that profenophos 50% EC provided 61.10 per cent control of leaf folder populations. Overall, this study highlights the advantages of drone sprayers for pest management. Drones provide more precise, consistent insecticide application, ensuring optimal coverage and reducing the variability associated with manual knapsack

Fi g 1. Comparative efficacy of drone vs. knapsack sprayer against leaf folder in paddy

Table 1. Comparative efficacy of drone vs. knapsack sprayer against leaf folder in paddy Spray equipment Treatments Per cent leaf damage First spray Second spray DBS 3 DAS 7 DAS 14 DAS Mean ROC DBS 3 DAS 7 DAS 14 DAS Mean ROC Drone sprayer Fipronil 5% 8.34 4.41 3.91 3.98 4.1 66.96 13.58 6.9 5.22 5.79 5.97 65.96 SC (16.78) (12.30)a (11.40)a (11.50)a (21.63) (15.22)a (13.20)a (13.92)a Profenophos 8.53 5.81 4.98 6.44 5.74 53.74 13.75 8.98 7.12 8.42 8.17 53.42 50% EC (16.98) (13.94)c (12.89)c (14.70)c (21.76) (17.43)c (15.47)c (16.86)c Knapsacksprayer Fipronil 7.98 5.12 4.12 5.98 5.07 59.14 12.92 7.89 6.85 6.98 7.24 58.72 5% SC (16.40) (13.07)b (11.71)b (14.15)b (21.06) (16.31)b (15.17)b (15.31)b Profenophos 8.65 5.98 4.98 8.84 6.6 46.81 13.20 9.12 8.60 8.98 8.9 49.25 50% EC (17.10) (14.15)cd (12.89)c (17.29)d (21.29) (17.57)cd (17.05)d (17.43)d Untreated Check 8.84 10.53 11.19 15.53 12.41 14.16 16.2 17.88 18.56 17.54 (17.29) (18.93)d (19.54)d (23.20)e (22.10) (23.73)e (25.01)e (25.51)e S.Em(±) NS 0.26 0.21 0.37 NS 0.45 0.46 0.35 C.V(%) 9.05 9.10 8.10 10.46 8.67 10.32 11.35 8.21 DBS – Day before spray, DAS – Days after first spray, NS – Non-Significant, ROC - Reduction over control, Figures in parenthesis are arc sine transformed values. Means showing similar alphabets do not differ significantly by DMRT (p=0.05)

Evaluation of drone technology in paddy ..... sprayers. Their ability to quickly cover large areas improves pest management efficiency, resulting in better overall field outcomes. Rice ear head bug (Leptocorisa oratorius) Drone applications of fipronil reduced damage by an average of 65.21 per cent in the first application and 76.95 per cent in the second, while knapsack sprayers achieved reductions of 59.03 per cent and 70.75 per cent. Profenophos applied via drone recorded damage reductions of 54.69 per cent in the first application and 64.84 per cent in the second, compared to 49.65 per cent and 55.98 per cent for the knapsack sprayer (Table 2). The drone's superior performance is largely due to its ability to ensure even and precise pesticide application, minimizing the variability common with manual spraying (Fig 2). The enhanced performance of drone sprayers is attributed to their ability to deliver uniform pesticide distribution and cover larger areas more efficiently. Drone technology ensures optimal pesticide application, while knapsack sprayers, relying on manual operation, often lead to uneven coverage, affecting pest control efficiency.

These findings are consistent with those of Singh et al. (2022), who demonstrated that fipronil 5% SC reduced ear head bug damage by 62.75 per cent, compared to a 58.43 per cent reduction with profenophos 50% EC. Prakash and Kunal (2020) also found fipronil to be more effective, reducing the pest population by 65.30 per cent, while profenophos achieved a 60.80 per cent reduction. Similarly, Patel et al. (2018) reported a 45.20 per cent reduction with fipronil, and Sharma et al. (2021) recorded a 54.55 per cent reduction with profenophos, further supporting fipronil's superior efficacy. In conclusion, this study highlights the advantages of drone sprayers in managing rice ear head bugs, offering precise, uniform pesticide application and more effective pest control compared to traditional knapsack sprayers. The superior results observed with drone spraying of both fipronil and profenophos emphasize the potential of drone technology to enhance pest management practices. Natural enemies The study assessed the effects of Fipronil and Profenophos applications on natural enemies such as spiders, coccinellids,

Supporting these findings, Lee et al. (2018) reported a control efficiency of 89.50 per cent with UAV spraying, significantly higher than the 73.20 per cent efficiency of knapsack sprayers. Zhang et al. (2019) and Meng et al. (2018) similarly noted superior pest control with UAVs, with Meng et al. highlighting a 24.70 per cent lower residue level and 19.60 per cent higher control efficacy against wheat aphids compared to knapsack sprayers. Rosedi and Shamsi (2022) observed that UAVs demonstrated 89.90 per cent control efficacy and covered 1.60 times more area than manual sprayers. Fipronil was found to outperform profenophos in controlling the rice ear head bug due to its specific action on the insect's GABA receptor pathways, causing more severe neurological damage and increased mortality. Profenophos, which affects acetylcholinesterase, can be less effective due to resistance issues and variable pest sensitivities.

Fig 2. Comparative efficacy of drone vs. knapsack sprayer against ear head bug in paddy

Table 2. Comparative efficacy of drone vs. knapsack sprayer against ear head bug in paddy Spray Treatments Number of nymphs and adults of ear head bug per hill equipment First spray Second spray DBS 3 DAS 7 DAS 14 DAS Mean ROC DBS 3 DAS 7 DAS 14 DAS Mean ROC Fipronil 5 3.74 1.42 1.42 1.72 1.52 65.21 4.63 1.48 1.19 1.81 1.56 76.95 Drone % SC (1.93) (1.19)a (1.19)a (1.31)a (2.15) (1.21)a (1.09)a (1.34)a Sprayer Profenophos 3.82 1.94 1.90 2.12 1.98 54.69 4.56 2.41 2.05 2.68 2.38 64.84 50% EC (1.95) (1.39)b (1.37)c (1.46)c (2.14) (1.55)b (1.43)c (1.64)c Fipronil 3.3 2.26 1.68 1.95 1.79 59.03 4.72 2.26 1.67 2.02 1.98 70.75 Knapsack 5% SC (1.82) (1.57)c (1.29)b (1.40)b (2.17) (1.50)c (1.29)b (1.42)b sprayer Profenophos 3.64 2.28 1.91 2.42 2.20 49.65 4.84 3.10 2.51 3.33 2.98 55.98 50% EC (1.91) (1.51)d (1.37)c (1.56)d (2.20) (1.76) d (1.59)d (1.82)d Untreated Check 3.24 3.76 4.07 5.28 4.37 5.13 6.11 6.84 7.38 6.77 (1.87) (1.94)e (2.01)d (2.30)e (2.33) (2.47)e (2.62)e (2.72)e S.Em(±) NS 0.09 0.10 0.13 NS 0.22 0.13 0.17 C.V(%) 10.21 8.71 10.98 10.78 8.25 11.64 10.32 11.68 DBS – Day before spray, DAS – Days after spray, NS – Non-Significant, ROC – Reduction over control. Figures in parenthesis are square root transformed values. Means showing similar alphabets do not differ significantly by DMRT (p=0.05)

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J. Farm Sci., 38(4): 2025 dragonflies and damselflies using both drone and knapsack sprayers. Across all natural enemy species, the untreated control plots consistently showed the highest populations. Among the treated plots, Fipronil applied via drone demonstrated better conservation of these beneficial organisms compared to both knapsack-applied Fipronil and Profenophos treatments. Spiders Initially, spider populations ranged from 1.96 to 2.40 spiders per hill. Three days after treatment the control group had the highest population (2.40 spiders/hill) followed by drone-applied fipronil (1.92 spiders/hill) showing that drones are safer for spiders. Knapsack-applied fipronil reduced the population to 1.73 spiders per hill, while profenophos, applied by drone

and knapsack, reduced it further to 1.48 and 1.40 spiders per hill (Table 3). After seven and fourteen days the same trend persisted, with the control group consistently having the highest spider population and fipronil applied via drone maintaining higher populations compared to other methods. These findings highlight that drone-applied fipronil is safer for spiders offering a more sustainable pest management solution in hill ecosystems. These findings are consistent with the observations of Singh et al. (2015), who reported the highest number of predatory spiders in the control plot, with 3.26 spiders per hill, while fipronil 5% SC treatment had the highest population among treatments, at 1.53 spiders per hill. Similarly, Shyamrao et al. (2022) confirmed that fipronil was safe for spiders. Additionally, when profenophos 50% EC was applied, drone sprayers again supported higher spider populations, with mean counts of 1.35 and 1.13 spiders per hill during the first and second sprays, compared to 1.20 and 1.11 spiders per hill with knapsack sprayers. These outcomes support Meng et al. (2018), who highlighted that UAV (drone) spraying improves pesticide efficiency and reduces residues, leading to better preservation

of beneficial predators like spiders. These findings emphasize the potential of drone spraying to maintain non-target species populations, contributing to a balanced and eco-friendly pest management approach. Coccinellids The study evaluated the efficacy of drone and knapsack sprayers for insecticide application on coccinellid populations. Before spraying, the population ranged from 1.73 to 1.95 coccinellids per hill. Three days after the first spray, the control recorded the highest population (1.84 coccinellids per hill), followed by fipronil via drone (1.61 coccinellids per hill), knapsack fipronil (1.47 coccinellids per hill), drone profenofos (1.40 coccinellids per hill), and knapsack profenofos (1.30 coccinellids per hill). By the seventh day, fipronil applied through drone maintained the highest population (2.09 coccinellids per hill), with the control highest overall (2.34 coccinellids per hill). After 14 days, the control remained highest (2.76 coccinellids per hill), and fipronil via drone preserved more coccinellids (2.25 coccinellids per hill) than knapsack application (2.13 coccinellids per hill). After the second spray, drone-applied fipronil resulted in 2.13 coccinellids per hill, while the control recorded the highest population (4.92 coccinellids per hill) (Table 4). Overall, drone sprayers, particularly with fipronil, were more effective and safer for preserving coccinellid populations, making drone technology a more eco-friendly alternative to knapsack sprayers. These results demonstrate that drones, with their precision and target-specific application, are less harmful to coccinellids. Firake et al. (2010) and Chormule et al. (2014) also emphasized the importance of reducing pesticide exposure to beneficial insects like coccinellids. Similar findings were supported by Meng et al. (2018) and Wei et al. (2020), who noted that UAVs (drones) deliver pesticides with minimal impact on beneficial insects, helping to maintain ecological balance by preserving populations of coccinellids. These studies highlight the effectiveness of drone spraying in protecting non-target species while maintaining pest control efficiency.

Table 3. Impact of drone vs. knapsack sprayer on spiders populations in paddy Spray equipment Treatments Number of spiders per hill First spray Second spray DBS 3 DAS 7 DAS 14 DAS Mean DBS 3 DAS 7 DAS 14 DAS Mean Drone sprayer Fipronil 5% SC 2.40 1.92 2.10 2 2.01 2.56 1.86 2.11 2.34 2.13 (1.55) (1.39)b (1.45)b (1.41)bc (1.60) (1.36)b (1.45) (1.53) Profenophos 2.21 1.48 1.67 2.10 1.75 2.64 1.74 1.88 2.12 1.91 50% EC (1.49) (1.22)d (1.29)e (1.45)b (1.62) (1.32)c (1.37)b (1.46)c Knapsack Fipronil 5% SC 2.27 1.73 1.98 1.91 1.87 2.79 1.61 1.81 1.92 1.83 sprayer (1.51) (1.32)c (1.41)c (1.38)cd (1.67) (1.27)d (1.34)b (1.39)d Profenophos 2.14 1.40 1.78 1.62 1.60 2.88 1.51 1.65 1.81 1.68 50% EC (1.46) (1.18)d (1.33)d (1.27)e (1.70) (1.23)de (1.29)c (1.35)e Untreated Check 1.96 2.40 2.98 3.14 2.84 4.25 4.67 4.92 5.23 4.94 (1.40) (1.54)a (1.73)a (1.77)a (2.17) (2.27)a (2.32)a (2.39)a S.Em(±) NS 0.07 0.09 0.08 0.10 0.11 0.13 0.15 C.V(%) 8.27 9.98 9.057 8.33 10.92 11.41 9.86 11.34 DBS – Day before spray, DAS – Day after spray, NS – Non-Significant, Figures in parenthesis are square root transformed values. Means showing similar alphabets do not differ significantly by DMRT (p=0.05

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Evaluation of drone technology in paddy ..... Table 4. Impact of drone vs. knapsack sprayer on coccinellids in paddy Spray Treatments Number of coccinellids per hill equipment Frist Spray Second Spray DBS 3 DAS 7 DAS 14 DAS Mean DBS 3 DAS 7 DAS 14 DAS Mean Drone sprayer Fipronil 5% SC 1.95 1.61 2.09 2.25 1.98 2.73 1.98 2.03 2.39 2.13 (1.39) (1.27)b (1.45)b (1.52)b (1.65) (1.40)b (1.42)b (1.54)b Profenophos 1.88 1.40 1.79 1.96 1.73 2.64 1.65 1.80 1.89 1.78 50% EC (1.37) (1.18)c (1.34)d (1.40)d (1.62) (1.28)d (1.34)c (1.37)cd Knapsack Fipronil 5% SC 1.81 1.47 1.95 2.13 1.85 2.58 1.79 1.88 2.01 1.89 sprayer (1.34) (1.21)c (1.39)c (1.46)c (1.61) (1.34)c (1.37)c (1.42)c Profenophos 1.73 1.30 1.68 1.82 1.66 2.51 1.25 1.67 1.96 1.63 50% EC (1.32) (1.14)d (1.29)e (1.35)e (1.57) (1.12)e (1.29)d (1.40)c Untreated Check 1.76 1.84 2.34 2.76 2.31 4.21 4.53 4.89 5.34 4.92 (1.33) (1.36)a (1.53)a

(1.66)a (2.17) (2.24)a (2.32)a (2.41)a S.Em(±) NS 0.06 0.07 0.09 0.10 0.11 0.12 0.15 C.V(%) 8.63 10.15 8.56 9.99 11.48 9.50 9.80 10.36 DBS – Day before spray, DAS – Day after spray, NS – Non-Significant, Figures in parenthesis are square root transformed values. Means showing similar alphabets do not differ significantly by DMRT (p=0.05) Table 5. Impact of drone vs. knapsack sprayer on dragonfly and damselfly in paddy Spray Treatments Number of dragonfly and damselfly per m2 equipment First spray Second spray DBS 3 DAS 7 DAS 14 DAS Mean DBS 3 DAS 7 DAS 14 DAS Mean Drone sprayer Fipronil 3.94 3.34 3.63 3.92 3.63 5.03 4.35 4.73 5.11 4.73 5% SC (1.98) (1.83)b (1.91)b (1.98)b (2.24) (2.09)b (2.17)b (2.26)b Profenophos 3.73 2.96 3.38 3.54 3.29 4.86 3.89 4.28 4.67 4.28 50% EC (1.93) (1.72)d (1.84)c (1.88)d (2.20) (1.97)d (2.07)d (2.16) d Knapsack Fipronil 3.85 3.16 3.44 3.72 3.44 4.95 4.15 4.51 4.87 4.51 sprayer 5% SC (1.96) (1.78)c (1.85)c (1.93)c (2.22) (2.04)c (2.14)c (2.21)c Profenophos 3.68 2.83 3.02 3.21 3.02 4.75 3.66 3.98 4.30 3.98 50% EC (1.92) (1.68)de (1.74)d (1.79)e (2.18) (1.91)e (1.99)e (2.07)e Untreated 3.89 4.52 4.97 5.42 4.97 6.86 7.25 7.87 8.29 7.81 Check (1.97) (2.13)a (2.23)a (2.33)a (2.71) (2.78)a (2.89)a (2.96)a S.Em(±) NS 0.17 0.15 0.14 0.22 0.24 0.25 0.26 C.V(%) 8.55 11.40 9.28 8.27 8.30 10.26 11.17 9.60 DBS – Day before spray, DAS – Day after spray, NS – Non-Significant, Figures in parenthesis are square root transformed values. Means showing similar alphabets do not differ significantly by DMRT (p=0.05)

Dragonflies and damselflies The study measured dragon and damselfly populations per square meter after applying Fipronil 5% SC and Profenophos 50% EC using drone and knapsack sprayers. For the first spray, Fipronil via drone resulted in a mean of 3.63 dragon and damselflies per square meter, while Profenophos via drone averaged 3.29 per square meter. Using a knapsack sprayer, Fipronil and Profenophos had mean of 3.44 and 3.02 per square meter, respectively. The untreated check had the highest mean of 4.97 per square meter. After the second spray, Fipronil via drone recorded a mean of 4.73 per square meter and Profenophos had a mean of 4.28. Fipronil via knapsack averaged 4.51 and Profenophos 3.98. The untreated check again showed the highest mean at 7.81 per square meter. Drone sprayers proved more consistent reducing pesticide exposure and preserving beneficial insects (Table 5).

UAVs reduce non-target impacts by improving pesticide targeting. Similarly, Chormule et al. (2014) reported that fipronil 5% SC supported the highest number of natural enemies, reinforcing the idea that drones are more beneficial in preserving non-target species like dragonflies and damselflies. Conclusions The findings of this study demonstrate the significant advantages of drone sprayers over traditional knapsack sprayers in managing key insect pests, particularly the rice leaf folder (Cnaphalocrocis medinalis) and rice ear head bug (Leptocorisa oratorius). Drone applications of fipronil 5 % SC and profenophos 50 % EC consistently outperformed knapsack sprayers, achieving more effective pest control due to their ability to deliver uniform and precise insecticide coverage over large areas. Fipronil was notably more effective than profenophos, owing to its systemic action, which provided enhanced control of both pests.

These results suggest that drones, with their precision, have a lesser impact on dragonflies and damselflies compared to In terms of natural enemy conservation, drone applications traditional knapsack methods. This aligns with findings by proved to be less disruptive. Populations of spiders, Meng et al. (2018) and Zhang et al. (2019), who noted that 411

J. Farm Sci., 38(4): 2025 coccinellids, dragonflies, and damselflies were better preserved when insecticides were applied via drones, compared to knapsack sprayers. Fipronil, when applied with drones, maintained higher populations of these beneficial species, further emphasizing the precision and reduced impact of drone technology on non-target organisms. Overall, the use of drones for insecticide application in paddy fields offers a dual benefit of superior pest control and better preservation of beneficial insects, contributing to a more

sustainable and eco-friendly pest management approach. The precision and efficiency of drone sprayers make them a highly effective tool for modern agricultural practices, helping to maintain ecological balance while ensuring optimal pest control outcomes. Acknowledgement I thank the chairman of my advisory committee and Professor and Head (IOF) Department of Plant pathology UAS, Dharwad for their technical guidance and support during study.

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DEVELOPMENT AND EVALUATION OF DRONE MOUNTED SPRAYER FOR PESTICIDE APPLICATIONS TO CROPS Yallappa D.1*, M. Veerangouda2, Devanand Maski3 Vijayakumar Palled4, and M. Bheemanna5 ..... *Yallappa D M. Tech. (Ag. Engg.) College of Agricultural Engineering, University of Agricultural Science, Raichur – 584104, Karnataka, INDIA* Email id: yallappa.raravi@gmail.com *Cell No: +91 9731699345 ..... ABSTRACT Application of crop protection materials is one of the crucial operations in agriculture to meet ever demanding food production. The drone mounted sprayer mainly consists of BLDC motors, LiPo (Lithium polymer) batteries, peticide tank, pump, and supporting frame. Six BLDC motors were mounted to hexa-copter frame to lift of 5 kg payload capacity. Two LiPo batteries of 6 cells 8000mAh were used to supply the necessary current required for the propulsion system. A 5 liter capacity conical-square shaped fluid tank was used to hold the pesticide solution. A 12 V DC motor coupled with pump was used to pressurize spray liquid and then to atomize in to fine spray droplets by means of four nozzles. A suitable aluminium supporting frame was used to mount the spray liquid tank, sprayer motor, spray and supporting legs (landing gears) for safe take-off and landing. The entire drone mounted sprayer operation controlling with the help of transmitter at ground level, HD FPV camera also provide at front down side of drone sprayer unit to monitoring the live spaying operation.

The developed drone mounted sprayer was evaluated for its field performance in groundnut and paddy crop and the average field capacity was found to be 1.15 ha h-1 and 1.08 ha h-1, respectively at a forward speed of 3.6 km h-1 and 1m height of spray. The cost of operation for groundnut and paddy crops using drone mounted sprayer has been worked out 345 and Rs. 367 Rs ha-1 respectively. The spray uniformity was increased with increase in height of spray and operating pressure. A VMD and NMD of spray droplet size were measured and it was found to be 345 and 270 µm, respectively in lab condition. This sprayer is very useful where human interventions are not possible for spraying of chemicals on crops including rice fields and orchard crops as well as crops under terrain lands. This technology greatly helpful for small farming community in reducing cost of pesticide application and environmental pollution but also biological efficacy of application technology. Key words: Drone, Drone mounted sprayer, UAV spraying, Pesticide spraying INTRODUCTION In India, Agriculture is a major sector of our economy but still it is far short of western countries when it comes to adapting latest technologies for better farm output. Farmers in developed world have started using agricultural drones equipped with cameras to improve the process of crop treatment. Kale et al. (2015) used agriculture drone for spraying fertilizer and pesticides. Architecture based on unmanned aerial vehicles (UAVs) which can be employed to implement a control loop for agricultural

applications where UAVs are responsible for spraying chemicals on crops. The process of applying the chemicals is controlled by wireless sensor network (WSN) deployed on the crop field. Huang et al. (2015) developed a low volume sprayer for an unmanned helicopter. The helicopter has a main rotor diameter of 3 m and a maximum payload of 22.7 kg. The helicopter used one gallon of gas for every 45 minutes. The method, system and analytical results from this study provide an extendable prototype that could be used in developing UAV aerial application systems for crop production management with higher target rate and larger VMD droplet size. Xue et al. (2016) developed an unmanned aerial vehicle based automatic aerial spraying system. The system used a highly integrated and ultra-low power MSP430 single-chip micro-computer with an independent functional module. This allowed route planning software to direct the UAV to the desired spray area. Dongyan et al. (2015) evaluated effective swath width and droplet distribution of aerial spraying systems on M-18B and Thrush 510G airplanes. In this study they evaluated the effective swath width and uniformity of droplet distribution of two agricultural airplanes, M-18B and Thrush 510G, which flew at 5 m and 4 m height, respectively. They concluded that flight height leads to the difference in swath width for M-18B Thrush 510G. At present in India, conventional methods of pesticide spray application leads to excessive application of chemicals, lower spray uniformity, deposition, and coverage;

resulting higher cost of pesticide as well as environmental pollution. Apart from these, there will be increased drudgery in field application and reduced area coverage, leading to increased cost of inputs as well as reduced effectiveness in controlling the pests and diseases. Keeping in view of these facts, a drone mounted sprayer was developed for application of pesticide sprays on to crops which improves coverage, boosts chemical effectiveness and makes spraying job easier and faster. 1. To develop a drone mounted sprayer and evaluate its performance for application of chemicals/pesticides. 2. To work out the economics of operating with drone mounted sprayer. MATERIALS AND METHODS The complete design was calculated by considering the total weight of the drone mounted sprayer as reference and these consideration parameters are payload capacity, design of supporting frame, landing gear, design of fluid tank, selection motors, battery, propeller, flight controller, transmitter and receiver. Development and pre-testing work has been carried out with the assistance of Maavan Aeronautics Pvt Ltd, Chennai, Tamil Nadu, India. Performance trials were conducted in the Research Farm of University of Agricultural Sciences, Raichur, Karnataka, India. The evaluation techniques used to find the performance of the drone mounted sprayer for the field conditions for the selected field crops viz., paddy and groundnut crops.

I. Construction and working mechanism The process of construction and mechanism involved in the operation of developed prototype sprayer are discussed here. a. Construction: As its prefix implies, a hexa-copter (“hexa” = six) is a type of drone setup in which there are six arms and each arm is connected to a single high-speed BLDC motor, These high speed motors are mounted at the outer end of aluminium tubes (500 x 25mm) which in turn are fixed to the outer edge of the glass fibre airframe (2mm thickness) using the arm mount. Battery, high speed motor support tube, flight controller with GPS antenna, ESC, FPV camera, sensors and other circuit boards are mounted on air frame plate. A 5 l capacity fluid tank is fixed at the bottom of the glass fibre supporting plate and outlet of the fluid tank pipe is connected to the inlet of the spray motor. An aluminium pipe (14x1.5mm) is bent in an inverted U shape for making supporting frame in which fluid tank, sprayer

motor and spray lance are mounted. Four nozzles are fixed on 1.3 m length of spray boom with 45 cm spacing between two nozzles. A 12 volts DC motor with pump is used to generate enough pressure to spray the liquid. Inlet liquid pipe of spray motor is connected to the outlet of fluid tank and outlet pipe is connected to sprayer nozzles. Landing gears are mounted at the bottom of drone mounted sprayer unit, which helps in safe takeoff and landing on ground surface before and after spraying operation. The overall specification of the developed drone mounted sprayer is presented in Table 1 and the assembling and development of drone mounted sprayer is shown in Plate. 1

Plate 1. Complete view of assembled drone mounted sprayer

b. Electrical power supply system: A 2 LiPo (Lithium polymer) batteries consisting of six cells – 8000 mAh are used and they are connected in parallel system to provide the required power for the operation of dronemounted sprayer. When the drone mounted sprayer system is switched on, the receiver starts receiving the transmitted frequency from transmitter/remote control. The transmitter gives commands for takeoff and landing as well as left, right, forward, backward and yaw movements. Electrical power is supplied equally to all the 6 BLDC high speed motors and they will start to rotate at specified speed which is controlled by the respective ESC, when the accelerator/throttle is increased or decreased in the transmitter. A 12 volts DC motor with pump is connected to the battery system through sprayer motor speed controller board for generating the pressurized spray liquid and also the outlet discharge rate can be directly controlled by changing the sprayer motor governor in the transmitter. The electrical circuit diagram is shown in Fig 1.

The spraying operation can also be directly controlled manually with the help of transmitter at the ground control station. FPV camera and AV display units are helpful for providing live footage of spraying operation in the AV display at the ground control station. It requires some amount of special operator training skills for the manual spraying operation.

Figure 1. Electrical circuit diagram of drone mounted sprayer

II. Performance evaluation of the developed drone mounted sprayer under laboratory condition The laboratory test are conducted to assess the different machine parameters such as discharge rate at different operating pressure, height of spray, swath width, uniformity of the spray and droplet size. The drone mounted sprayer was operated at different heights at different operating pressure. a. Discharge and Pressure of spay liquid: The discharge and pressure from the sprayer was measured at three levels of operating pressure mode by rotating regulator device in transmitter/remote controller. The drone mounted sprayer unit was tested at three different operating pressure modes and the spray volume was collected in measuring cylinder for one minute duration.

Table 1. Specifications of the drone mounted sprayer Sl. No. 1 2 3 4 5 6 7 8 9 10

Parameters

Value

Overall dimensions, 420×1300×450 (L × W × H), mm Weight, kg 6 Power source for Battery power spraying Pump discharge, l min-1 2.5 Regulator in Pressure control device transmitter Number of nozzles 4 450 Nozzle spacing, mm (Adjustable) Type of nozzle Flat fan Spray lance length, mm 1300 Tank capacity, l 5 Plate 2. Measurement of discharge rate and spray uniformity in the laboratory

b. Spray uniformity: The drone mounted sprayer unit was kept and operated at five different heights viz., 500 mm, 750 mm, 1000 mm,1250 mm and 1500 mm (Padmanathan et al., 2007) from the patternator and spray liquid at the collecting pipes of the patternator was collected and the quantity of liquid from each of 53 channels was measured. c. Spray liquid loss: Spray liquid loss may accrue due to effect of wind velocity and air temperature. The developed drone mounted sprayer unit was operated at different heights and pressure from the patternator and spray liquid at the collecting pipes of the patternator was collected and the quantity of liquid from each of 53 channels was measured. d. Droplet size and density: The spray was coloured with water soluble methylene blue of 0.75 percent concentration used. Photographic paper having size of 50x50 mm was placed on each plan table and at a horizontal distance of 25000 mm. It was placed at 1000 mm height from ground surface in open yard. The drone mounted sprayer was operated at height (from top surface of table), speed and discharge rate of 1000 mm, 6 km h-1 and 1.60 l min-1 respectively. The sizes of the water droplets on the photographic paper were determined through trinocular microscope equipped with an ocular after

allowing a minimum period of 24 h for complete spreading of droplets on the sampling surface. From the individual photographic sample, sixty water droplets were selected and the droplet diameters were computed for volume median diameter (VMD), number median diameter (NMD) size was noted.

III. Field evaluation drone sprayer for selected field crops.

mounted

The performance evaluation of drone mounted sprayer on paddy and groundnut crops has been carried out at Research Farm of University of Agricultural Sciences, Raichur during the year 2016-17. During field trials, the agronomic data pertaining to paddy and groundnut crops such as row to row spacing, plant to plant spacing, height of crop, leaf area index and stage of crop were noted. For spraying operation, the recommended chemical solution as per the plant requirement was prepared separately in the tank. The data on speed of operation, swath width, discharge rate, field efficiency, application rate, flying endurance and time losses were measured and noted for the paddy and groundnut crop.

Plate 3. Performance evaluation of drone mounted sprayer in paddy and groundnut crop

99.50

Evaluation of developed drone mounted sprayer under laboratory conditions for discharge rate, droplet size, droplet density, swath width and spray uniformity are analyzed and discussed. Field performance evaluation of the developed drone mounted sprayer in the field condition is also presented. The cost-economic of the unit is found out and salient features are enlightened.

99.00

1.37 1.78 50

75 100 125 150

1.92

Height of spray, cm

Figure 2. Effect of height of spray and operating pressure on swath width

1.37

98.50

1.78

98.00 50

75 100 125 150

1.92

Heigt of spray, cm

Figure 4. Effect of height of spray and operating pressure on spray uniformity

The spray uniformity increased with increase in height of spray and operating pressure. Spray liquid loss, %

Swath width, mm

4000 3000 2000 1000 0

Spray uniformity, %

RESULTS AND DISCUSSION

5 4 3

1.37

2

1.78

1

1.92

0 50

75

100

125

150

Heigt of spray, cm

Discharge, ml min-1

It was observed that the swath width was increased by increasing the height of spray and operating pressure. 2000 1500 1000

1.37

500

1.78

0

1.92 50

75 100 125 150

Height of spray, cm

It was observed that there was less spray liquid loss due to powerful backspin airflow produced by the propeller during spraying operation in spray patternator. Table 2 . Performance evaluation of drone mounted sprayer in paddy and groundnut crop Sl No

1 2

Figure 3. Effect of height of spray and operating pressure on discharge

3 4

It was observed that the discharge increased by increasing the operating pressure. The height of spray does not influence the discharge rate during the laboratory trials.

5 6 7

Parameter

Forward speed, km h-1 Width of spraying, m Actual field capacity, ha h-1 Theoretical field capacity ha h-1 Field efficiency, % Application rate, l ha-1 Cost of operation , Rs ha-1

Groundnut

Paddy

3.6

3.6

5.10

5

1.15

1.08

1.83

1.80

62.84

60.00

55.15

55.5

345

367

The developed drone mounted sprayer was evaluated for its field performance in groundnut and paddy crop and the average field capacity was found to be 1.15 ha h-1 and 1.08 ha h-1, respectively at a forward speed of 3.6 km h-1 and 1m height of spray. The cost of operation for groundnut and paddy crops using drone mounted sprayer has been worked out 345 Rs ha-1 and 367 Rs ha-1 respectively. The drone mounted sprayer worked satisfactorily for the selected field crops of groundnut and paddy crops for spraying operation and reduced the drudgery involved. SUMMARY AND CONCLUSION This technology is very useful where human interventions are not possible for spraying of chemicals on crops including rice fields and orchard crops as well as crops under terrain lands. It helps in improves coverage, boosts chemical effectiveness and makes spraying job easier and faster. Developed drone mounted sprayer can takeoff maximum 5.5 l and endurance 16 min. but need to be design 15 l of payload capacity and 30 minutes endurance for chemical spraying in field crops. REFERENCES Huang, Y., Hoffman, W. C., Lan, Y., Bradley, K., Fritz, B. K. and Thomson, S. J., 2015, Development of a low-volume sprayer for an unmanned helicopter. J. Agric. Sci., 7(1): 148-153. Huang, Y., Hoffmann, W. C., Lan, Y., Wu,W. and Fritz,. B. K., 2009, development of a spray system for an unmanned aerial vehicle platform. Applied Engineering in Agriculture, 25(6): 803-809.

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Drone-based field demonstrations and farmers’ response towards precision spraying technology in Jammu and Kashmir 1

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Abstract The Agricultural Technology Application Research Institute (ATARI), Zone I, facilitated drone demonstrations across different districts of Jammu division to promote awareness and adoption among farmers. In this project, KVK- Jammu has facilitated the drone with a target of covering the 250 hectares of land through drone demonstrations. This target was successfully achieved with 184 demonstrations, covering 256 hectares area and reaching 18,599 farmers. Among different demonstrations, the application of nano urea and herbicide spraying constituted the highest share (33%) whereas among the crops the wheat and paddy showed the highest share (35%). The maximum demonstrations and farmers gathering took place during 2025 due to large-scale awareness campaigns and training programmes. These results revealed that it helps in time savings, reduced labour requirement, and more judicious application of inputs such as glyphosate, nano urea plus, and sticker formulations. In this aspect, the majority of the farmers agreed on better performance of this technology in comparison with others and also improved their knowledge by 60-70%. This helps in effective management of Saccharum spontaneum (Sarkanda) weed by optimized chemical use. Although, the several constraints faced by farmers for individual ownership of drones may be due to small landholdings and financial conditions but they showed strong interest in accessing drone services through government-supported schemes. These findings indicate that drone technology can significantly enhance operational efficiency and promote precision agriculture in the region, highlighting the need for policy support and service-based delivery models to strengthen adoption. Keywords: Awareness campaigns, drone demonstration, drone technology, nano urea and precision agriculture

Introduction Agriculture remains the backbone of the Indian economy, supporting the livelihoods of a large rural population. However, the sector is increasingly challenged by shrinking landholdings, rising labour costs, climate variability, and the continued reliance on traditional crop management practices [1] . These constraints are particularly evident in the Jammu division of Jammu and Kashmir, where fragmented farms and undulating terrain limit the efficiency of conventional agricultural operations. In such situations, adoption of modern technologies becomes essential to enhance productivity, reduce costs, and ensure sustainability. The drone technology has recently emerged as an innovative tool in precision agriculture. Unmanned Aerial Vehicles (UAVs) enable uniform and targeted application of crop protection

chemicals and nutrients, saving time and labour while reducing excessive input use [2]. Compared to manual spraying, drone-based application improves coverage, minimizes human exposure to chemicals, and ensures timely operations, particularly in areas where access is difficult [3]. Despite these advantages, awareness and adoption of drone technology among small and marginal farmers remain limited due to high initial costs, lack of technical knowledge and limited opportunities [4]. To bridge this gap, the Agricultural Technology Application Research Institute (ATARI), Zone I, initiated and supported drone demonstrations across different districts of the Jammu division starting from 2023 to 2025. These demonstrations aimed to familiarize farmers with drone-based spraying and to assess its practical feasibility under local farming

conditions. Understanding farmers' perception, response, and willingness to adopt such advanced technologies is crucial for scaling up their use. Therefore, the present study was undertaken to evaluate the impact of drone demonstrations in farmers' fields with special reference to time efficiency, input optimization, and overall acceptance of the technology in the region. Objectives 1. To demonstrate the effectiveness of drone based spraying in Farmers' field. 2. To compare drone spraying with knapsack and boom sprayer in term of time, cost and efficiency 3. To assess Farmers' perception, satisfaction and willingness to adopt drone technology Methodology The study was conducted from 2023-25 to document dronebased spraying demonstrations organized in selected districts of Jammu division of Jammu and Kashmir by Krishi Vigyan Kendra, Jammu, Jammu and Kashmir, India under the technical guidance of Agricultural Technology Application Research Institute (ATARI), Zone I. In this project, the drone was provided to KVK- Jammu for field demonstration with a

target of covering the 250 hectares of land. The data recorded included date, location, number of farmers participated, area covered (hectare) and purpose of application. The entries without reported farmer participation were excluded from participation totals but included in area estimation. The data were compiled yearwise and purpose-wise. In this context, descriptive statistical tools such as totals, averages and percentages were used for analysis. The results were then interpreted in the context of extension outreach and technology dissemination. Krishi Vigyan Kendra Drone Project: This was launched by ICAR-ATARI Zone-I in 2022 under the Ministry of Agriculture and Farmers Welfare to promote the drone technology in agriculture sector through Krishi Vigyan Kendras (KVKs) in northern states, including Jammu and Kashmir [5]. This project covers 20 KVKs with 10 drones deployed and 12 rural youth trained as drone pilots. Under this project, 424 field demonstrations were conducted covering 624.8 ha with reaching over 6000 farmers [6]. This aims to improve precision spraying of fertilizers and pesticides, enhance adoption of drone-based agricultural practices in the region. The Agricultural drone or UAV (Agribot by IoTech World) used for field demonstration was provided under Krishi Vigyan Kendra Drone Project which mainly consists of a hexacopter with 4 ha/hr efficiency, maximum take off weight of 25 Kg along with tank volume of 10 L, move upto a maximum height of 0-30 m, work efficiently at 0-50 °C, fly at maximum speed of 0-10 m/s, maximum flight time without payload is 15-20 minutes, move within a range of 2 Km, spray width is 3 m, maximum discharge rate is 0.85 L/minutes per nozzle, battery capacity is 16000 mH, battery voltage 22.2 or 44.4V and life is 300 cycles [7]. The various drone demonstrations were shown to the institutional and farmers field as shown in the given images: www.extensionjournal.com

Fig 1: Agricultural drone demonstrations were shown at the institutional and Farmers' field

Results and Discussion The results revealed a steady expansion of drone-based agricultural demonstrations in Jammu division over the study period. A total of 184 demonstrations were conducted across three years covering 256 hectares. Direct farmer participation was recorded with a reach of 18,599 farmers, indicating substantial participation. Year-wise Trend: The number of demonstrations increased from 3 in 2023 to 74 in 2024 and peaked at 107 in 2025, showing rapid expansion of drone-based extension activities. Interestingly, farmer participation was highest in 2025 (10,496 farmers), largely due to mega awareness events such as institutional and training programmes (Figure 2). This indicates that large-scale campaigns significantly enhance outreach impact compared to routine farm demonstrations. The increasing trend reflects growing institutional emphasis on precision agriculture and positive farmer response toward emerging technologies.

Fig 2: Year-wise distribution of drone demonstrations (2023-25)

Farmers' perception towards drone technology: The results showed that the majority of the farmers show a positive response towards the spraying application through drones. In this aspect, the 88% of the farmers agreed that drone application saves time, while 84% of farmers reported that it also provides the uniform spray coverage. Similarly, the 81% of the farmers believed that drone spraying reduces exposure to chemicals and 91% considered it a useful technology (Table 1). This positive response may be due to time saving, reduced labour cost, uniform spray distribution and improved safety measures. 322

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Table 1: Farmers' perception towards drone spraying technology (2023-25) Statement Drone spraying saves time Drone spraying provides uniform spray coverage Drone spraying reduces farmers exposure to chemicals Drone technology is useful in agriculture

Increase in Farmers' knowledge by drone demonstrations: The results showed an increase in Farmers' knowledge regarding drone technology after the field demonstrations. The awareness about agricultural drones increased from 29% to 85% after the demonstration while the knowledge about the nano-urea spraying through

Agree (%) 88 84 81 91

Neutral (%) 8 11 13 6

Disagree (%) 4 5 6 3

drones has increased from 24% to 88%. The similar results were obtained regarding the fungicides and pesticides as well (Table 2). This improvement may be attributed to practical field demonstrations, direct interaction with the farmers, better understanding of the technology and directly seeing the results.

Table 2: Effect of drone demonstrations on Farmers' knowledge level (2023-25) Knowledge aspect Awareness about agricultural drones Knowledge about nano-urea application through drones Knowledge about fungicide and pesticide application through drones Knowledge about advantages of drone spraying

Comparison of different spraying methods: The results clearly indicate that the drone sprayer had outperformed the other spraying methods with highest field capacity (3.03 ha/hr), lowest water requirement (25 L/ha) and minimum time taken (20 min/ha). In comparison, the knapsack sprayer showed the lowest efficiency (0.40 ha/hr, 500 L/ha, 150 min/ha), while the boom sprayer performed moderately

Before demonstrations (%) 29 24 27 25

After demonstrations Knowledge (%) gain (%) 85 65.88 88 72.72 83 67.46 92 72.83

(0.60 ha/hr, 600 L/ha, 100 min/ha). The drone sprayer is more efficient because it sprays chemicals from the air with GPS-controlled precision, ensuring uniform coverage, reducing water and chemical use, reducing labour requirement and also saves time as compared to other spraying methods (Table 3).

Table 3: Comparative performance of different spraying methods Parameters Field capacity (ha/hr) Labour requirement Water requirement (L/ha) Time required (min/ha) Uniformity of spray Cost of operation (Rs/ha) Mode of operation Water saving (%)

Drone sprayer 3.03 1 25 20 Very high 1000 By remote and GPS 95-96%

Purpose-wise Analysis: As shown in fig. 3a, the spraying of nano-urea and weedicide constituted the highest proportion (33%) of total demonstrations. This suggests that precision nutrient management and weedicide applications are a primary focus area in drone deployment. The fungicide (8%) and pesticide (10%) applications further demonstrate the versatility of drone technology in crop protection. Awareness-only campaigns (17%) played a crucial role in sensitizing farmers and building initial confidence toward the technology.

Knapsack sprayer 0.40 2 500 150 Medium 1250 Manually 16-17%

Boom sprayer 0.60 2 600 100 High 1500 Tractor mounted -

Crop-wise Focus The crop demonstrations consist of wheat and paddy (35%) each, which were the major crops covered, reflecting their dominance in the region. Limited demonstrations on maize indicate potential scope for expansion in diversified cropping systems (fig. 3b). The concentration of activities on major cereals suggests that drone services are currently aligned with high-area crops where scale advantages are significant.

Fig 3: The purpose wise (a) and crop wise (b) demonstrations of drone application (2023-25) www.extensionjournal.com

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Extension Perspective: The data indicate that institutionalled demonstrations are effective tools for technology diffusion. High farmer participation in organized events shows increasing acceptance, though small landholdings may restrict individual ownership. Therefore, custom hiring models and government-supported service systems may be more feasible for widespread adoption. Some of the government schemes which make the feasibility of small scale farmers to use drones: 1. Sub-Mission on Agricultural Mechanization (SMAM): This scheme was launched in 2014-15 by the Ministry of Agriculture and Farmers Welfare to increase the reach of farm mechanization for small scale and marginal farmers. This program provides 50% subsidy for small scale farmers and 40% subsidy for women farmers. In this scheme, the funds amount of Rs. 141.39 crores released towards drone promotion. In this 263 agri-drones have been procured by 193 institutions of ICAR across the country and 263 personnel from these institutions have undergone drone pilot training [8]. 2. Custom Hiring Centers (CHC) Scheme: In this scheme, the different centers were opened by Government of India to provide the farm machinery and equipment for small and marginal farmers on a rental basis. These are mainly formed to help the modern agriculture practices are affordable and accessible. In this scheme, 44607 CHCs with 139319 agricultural machineries for renting out are registered on mobile app in which total of 114461 farmers are registered on this mobile app named CHC App [9]. 3. Namo Drone Didi (NDD) Scheme: It is launched in 2023 by the Government of India for empowering women-led Self-help Groups by provide the drone technology for agricultural services. The scheme provides 80% subsidy on drone costs up to 8 lakhs and 20% can be financed

through loans under Agriculture Infrastructure Fund. This scheme has an outlay of Rs.1261 crore from the period 2023–26 by targeting the distribution of 15000 drones to selected SHGs in which only 500 drones have been distributed [10]. Overall, the study confirms that drone demonstrations have moved beyond experimental exposure and are gradually integrating into mainstream extension strategies.

systems. Acknowledgement All the authors would be very grateful to acknowledge the funding source of the study is ICAR-ATARI, Punjab Agricultural University, Ludhiana. References 1. Satish S, Shirwal S, Abishek A, Maheshwari M, Murali M. Application of drones in precision agriculture: A review on benefits and challenges. Journal of Experimental Agriculture International. 2025;47(7):516-531. 2. Sahu M, Thapliyal S, Singh D. UAV technology in precision agriculture. Wisdom Leaf Press Journal. 2024;1(2):1-5. 3. Zhang Y, Li X, Chen H. Sustainable crop protection through integrated technologies: UAV-based detection and adaptive spraying. Scientific Reports. 2025;15:35748. 4. Seo S, Lee K. Density-driven multi-agent coordination for efficient farm coverage and management in smart agriculture. arXiv. 2025. 5. Indian Council of Agricultural Research. Krishi Vigyan Kendras – KVK network and technology dissemination activities. Ministry of Agriculture and Farmers' Welfare; 2025. 6. Agricultural Technology Application Research Institute, Zone I. Drone technology demonstrations and field adoption data report. Ludhiana: ICAR-ATARI Zone I; 2025. 7. IoTechWorld Avigation Pvt Ltd. AGRIBOT MX V1 brochure and technical specifications. IoTechWorld; 2024. 8. Government of India. Operational guidelines of the Sub-Mission on Agricultural Mechanization (SMAM). Ministry of Agriculture and Farmers Welfare, New Delhi; 2018. 9. Government of India. Custom Hiring Centres under the Sub-Mission on Agricultural Mechanization (SMAM). Ministry of Agriculture and Farmers Welfare, New Delhi; 2018. 10. Government of India. Guidelines of Namo Drone Didi Scheme. Ministry of Rural Development, New Delhi; 2023.

Conclusion The study documented that the target of covering of 250 hectares of land through drone demonstrations was successfully achieved by conducting 184 drone demonstrations between 2023 and 2025 in Jammu division, covering 256 hectares and reaching 18,599 farmers. Demonstrations increased substantially during 2024 and 2025, indicating growing institutional support and farmer interest. The nano urea and weedicide applications were the dominant operational purposes, particularly in wheat and paddy crops. The large-scale awareness programmes significantly enhanced outreach impact. Henceforth, the findings suggest strong potential for scaling drone-based custom hiring services in the region. Continued extension support and policy backing will be critical for sustained adoption of drone technology in smallholder farming www.extensionjournal.com

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RESEARCH ARTICLE

Advancements and trends in UAV utilization for crop protection: a bibliometric analysis

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ICAR-Directorate of Onion and Garlic Research, Pune, India; bICAR-National Institute of Abiotic Stress Management, Baramati, India ABSTRACT

ARTICLE HISTORY

Unmanned aerial vehicles (UAVs), or drones, have become pivotal tools in precision agriculture, particularly for aerial spraying and crop health monitoring. Their adoption addresses farmers' health issues related to manual pesticide exposure and ensures the timely execution of crop protection activities. This paper presents a systematic investigation and comprehensive bibliometric analysis of the scientific literature on UAV utilization in crop protection, spanning from 2007 to 2024. Using Scopus data analyzed with Bibliometrix and VOSviewer, the study identified 439 relevant documents to reveal key research trends and influential collaboration networks. The analysis confirms a marked increase in research output, with China and the USA leading globally in terms of publication volume and citation impact. Core research themes centre on integrating advanced technologies, such as remote sensing, deep learning and artificial intelligence, to enhance the precision of applications. The findings underscore the potential of UAVs as an efficient, safer, and more sustainable alternative to conventional methods. However, challenges specific to the Indian agricultural context, such as small landholdings and high initial costs, are highlighted, offering valuable insights for other developing agrarian economies.

Received 16 February 2025 Accepted 26 March 2026 KEYWORDS

Agrochemical spray; bibliometrics; crop protection; sustainability in agriculture; UAV

Introduction

The agricultural sector remains the backbone of the Indian economy, accounting for more than 60% of employment. To meet the demands of a rapidly increasing global population, which is projected to reach approximately 10 billion by 2050 (Dutta & Goswami, 2020). The enhancement of agricultural productivity and efficiency is imperative to ensure worldwide food security (Hunter et al., 2017). Consequently, precision agriculture (PA) is gaining significant attention, utilizing cutting-edge technologies for data collection, analysis and communication to implement customized crop management strategies. These practices aim to optimize crop yield, minimize the wastage water and nutrients to mitigate adverse environmental impacts (Boursianis et al., 2020; Sishodia et al., 2020). In this context, UAV-based crop protection represents a transformative approach for modern agriculture by enabling precise, timely and site-specific agrochemical applications. This technology not only improves spraying efficiency and reduces chemical wastage but also minimizes the occupational exposure of farmers to hazardous pesticides, thereby enhancing environmental sustainability and human health safety. Consequently, understanding the global research landscape and technological trends in UAV-enabled crop protection is essential for guiding future innovations, policy formulation, and large-scale adoption, particularly in developing agrarian economies. Despite the potential of PA, farmers in India largely use conventional methods for seed planting, composting and pesticide application. These traditional techniques are often time-consuming and less effective, particularly for chemical spraying (Rolle et al., 2015). Furthermore, the manual application of pesticides exposes farmers to health issues such as tumors, allergies and hypersensitivity (Damalas & Koutroubas, 2016). Globally, pests, diseases and weeds are estimated to cause 20%–40% losses in major food crops annually, resulting in economic losses exceeding USD 220 billion due to plant diseases and approximately USD 70 billion due to invasive insects CONTACT Rajiv B. Kale

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(Junaid & Gokce, 2024). At the same time, conventional pesticide spraying methods often suffer from low application efficiency, with nearly 30%–50% of agrochemicals lost due to spray drift and off-target deposition. In contrast, UAV-based spraying systems can improve application precision, reduce chemical use by 15%–30%, highlighting their growing importance in sustainable crop protection. The challenges faced by conventional farmers were exacerbated by the COVID-19 pandemic, highlighting the urgent need for technological advancement in crop management (Varshney et al., 2020). Unmanned aerial vehicles (UAVs), also known as drones, have emerged as pivotal tools to address these issues (Hafeez et al., 2023). They are now extensively used in agriculture for tasks such as crop monitoring, estimating crop yield and agrochemical applications (Anthony et al., 2014; Bendig et al., 2012; Hiremath et al., 2024). Drones are expected to become an important component of Agriculture 4.0 by supporting the integration of the IoT, big data, artificial intelligence and robotics across agricultural production and supply chains. The scientific literature on the use of UAVs in crop protection has significantly increased over the last decade, necessitating quantitative review methods to understand the knowledge structures and research trends in this emerging field. Prior studies have provided general bibliometric reviews on the use of UAVs in agriculture and forestry (Raparelli & Bajocco, 2019; Rejeb et al., 2022). A focused and comprehensive bibliometric analysis concentrating specifically on the advancements and trends in UAV utilization for crop protection, particularly for agrochemical spraying, remains underexplored. This study distinguishes itself by systematically analyzing literature spanning from 2007 to 2024 to map the intellectual structure, influential contributors and key thematic clusters related solely to UAV-based crop protection. The novelty lies in its detailed synthesis of crucial application parameters such as flight height, nozzle type, and pesticide formulation and its explicit discussion of the opportunities and adoption challenges in the Indian context. The aim of the present study is to provide a systematic and comprehensive bibliometric analysis of the global scientific output concerning the application of UAVs in crop protection and spraying. The objectives are to: (1) map key research trends, influential authors, and collaborative networks using quantitative bibliometric tools; (2) synthesize the thematic literature on the optimization factors for UAV spraying and crop monitoring; and (3) highlight the opportunities and challenges specific to the Indian agricultural context, offering valuable perspectives for other developing agrarian economies.

- Methodology 2.1. Retrieval of data Scopus, a leading database for scientific literature, was used for comprehensive bibliometric analysis. This study focused on identifying the literature concerning the use of UAVs for crop protection and spraying. Boolean operators ‘AND’ and ‘OR’ were employed to create a comprehensive advanced search setup in Scopus. The search strategy for data retrieval from Scopus was as follows: (TITLE-ABS-KEY (‘drone’) OR TITLE-ABS-KEY (‘unmanned aerial vehicle’) OR TITLE-ABS-KEY (‘UAV’) OR TITLE-ABS-KEY (‘unmanned aircraft system’) OR TITLE-ABS-KEY (‘remotely piloted aircraft’) AND TITLE-ABS-KEY (‘crop protection’ OR ‘herbicide spraying’ OR ‘herbicide’ OR ‘fungicide’ OR ‘biostimulant’ OR ‘pesticide spray’)). A total of 489 documents, spanning from 2007 to 2024, were retrieved and exported from Scopus in the CSV format for further analysis.

2.2. Screening of data This study employed a bibliometric analysis approach to examine research focused on UAV use for agricultural spraying and crop protection. This investigation followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. The retrieved articles in the CSV file were screened to remove duplicates and irrelevant literature. Documents that were non-English, not peer-reviewed, non-academic, or not focused on UAV spraying/crop protection were excluded from the dataset (Figure 1 and Table 1).

2.3. Bibliometric analysis The cleaned data were then analysed using Bibliometrix R package using its web-interface tool Biblioshiny (Aria & Cuccurullo, 2017) and VOSviewer version 1.6.20 (Van Eck & Waltman, 2010), both renowned for their

Figure 1. PRISMA flow diagram illustrating the study selection process for the bibliometric study.

Table 1. The features of dataset used in present analysis. Dataset features Document contents Timespan Documents Annual growth rate % Document average age Average citations per doc Document contents Keywords plus (ID) Author's keywords (DE) Authorship details Authors Authors of single-authored docs Authors collaboration Single-authored docs Co-authors per doc International co-authorships %

2007:2024 439 25.1 3.4 20.24 2343 1373 1680 14 14 4.91 25.13

user-friendly interface and clear visual representation in bibliometric studies. The data were analyzed for various parameters, such as annual publication output, influential authors, journal citations, intercountry collaboration, keyword's co-occurrence analysis, etc.

2.3.1. Publication trends and relevant sources, affiliations and authors Annual publication output: The number of documents published per year was quantified to identify growth trajectories and publication trends in the use of UAVs for crop protection. Influential contributors and sources: this analysis was performed to identify the 'most relevant authors' where authors were ranked by the highest total number of publications; 'most relevant affiliations' institutions were identified by the

highest count of documents, and the 'most relevant sources' here journals were ranked by their contribution volume to the dataset.

2.3.2. Corresponding author countries, most cited countries and most cited documents To assess the global landscape of research and its impact, the following analyses were conducted. 'Corresponding author countries and collaboration': the documents were categorized based on the country of the corresponding author. A distinction was made between Single-Country Publications (SCP) and MultiCountry Publications (MCP) to map the extent of international collaboration in the field. 'Most cited countries': countries were ranked by the total number of citations received by their publications to quantify their global research influence. 'Most globally cited documents': a list of the most highly cited individual research papers was generated to identify key influential documents that have significantly shaped the field. 2.3.3. Word cloud map, trend topics and co-occurrence analysis of keywords 'Word cloud map': a word frequency analysis was performed on the titles, abstracts, and author keywords of the dataset. The most commonly occurring terms were visualized in a word cloud map to provide a visual representation of the prevalent research themes and focus areas within the literature. Trend topics analysis was conducted to explore the temporal evolution of key research themes in UAV-based crop protection. Author keywords extracted from the Scopus dataset were analyzed using the Bibliometrix package in R (Aria & Cuccurullo, 2017). Keyword frequencies were calculated and mapped across different time intervals. Keyword co-occurrence analysis was employed to identify and visualize the key thematic clusters and intellectual structure of the research field. This analysis was executed using VOSviewer (v1.6.20), a tool specifically designed for constructing and visualizing bibliometric maps. From the total pool of 1375 keywords identified in the dataset, a selection was made based on a minimum frequency criterion. Only the 37 keywords that appeared a minimum of seven times in the document set were used for the analysis.

- Results The present section provides bibliometric analysis of data retrieved from the Scopus regarding the adoption of UAVs in crop protection. A total of 439 documents were remained after screening and processing and were used for further bibliometric analysis. These documents were comprised of articles (287), book chapters (15), conference papers (102), reviews (28), conference reviews, data papers, notes and short surveys, among others.

3.1. Publication growth and relevant sources, affiliations, and authors Figure 2 reveals the significant trends and key contributors to this emerging field. Figure 2A demonstrates a multi-fold increase in annual scientific production from only one publication in 2007 to 90 publications in 2023, with an annual growth rate of over 25%, highlighting the growing academic interest and research output in the use of UAVs for crop protection. Figure 2B highlights the most relevant sources from which this research is being published. These 439 documents were published in more than 200 journals. The leading journals are Remote Sensing, Agronomy and Pest Management Science, with 20, 19 and 18 documents, respectively, indicating a strong intersection between UAV technology and precision agriculture. The diversity sources like Computers and Electronics in Agriculture, Remote Sensing, Crop Protection reflects the interdisciplinary nature of this research, integrating insights from plant science, engineering and environmental studies to develop comprehensive UAV-based spraying solutions.

The institutional/affiliation analysis in Figure 2C reveals that China Agricultural University is the most prolific, with 76 publications. Other notable institutions include South China Agricultural University and North Carolina State University, which point to a strong academic focus on integrating UAV technology into agricultural practices. With five Chinese institutions ranking in the top ten affiliations, the bibliometric data clearly indicates the substantial research output and dedicated focus of China on advancing UAVs in crop protection. Tamil Nadu

Figure 2. (A) Annual scientific production. (B) Most relevant sources. (C) Most relevant affiliations. (D) Most relevant authors.

Agricultural University from India also features among the top ten most prolific affiliations in this research domain. Finally, the most relevant authors are shown in Figure 2D, indicating that Lan Y is the most relevant author, with 18 publications, followed by Xue X, with 11 papers. Both of these authors are from China, further emphasizing China's leadership in this research domain. Researchers from 58 countries have studied the UAVs in crop protection. Among these, China, the USA and India are the top three countries in terms of publication output.

3.2. Corresponding author countries and international collaboration The present bibliometric analysis offers a comprehensive overview of the global research landscape on UAV-based spraying, highlighting the distribution of corresponding authors by country, the most influential countries in terms of citations, the top-cited publications, and the dominant research themes within this field. Figure 3A reveals that China leads significantly in the number of publications, both in single-country publications (SCP) and multi-country publications (MCP), underscoring its dominant role in this research field. The USA is the second most prolific nation, also exhibiting high output in both categories. India and Brazil also contributed notably, although their MCP contributions were comparatively lower, suggesting a greater emphasis on domestically focused research efforts within their respective agricultural contexts. More than 25% of the articles are MCP which reflects the substantial international collaboration in this research domain. The world collaboration map clearly highlights a central, high-frequency collaboration axis between the USA and China (Figure 3B). This demonstrates that the two countries form the most robust partnership within the global scientific research network in this domain. China, which is the overall leading country in publication output, acts as a pivotal node in the network, maintaining active and frequent collaboration with numerous countries. Author co-occurrence analysis was performed using Biblioshiny in the domain of UAVs for crop protection (Figure 3C). The major clusters (red and green) are centred around the most prolific authors, such as Lan Y, Xue X and Zhang S. This cluster reflects the strong domestic research community and high collaboration frequency, primarily among Chinese authors.

Figure 3. (A) Corresponding author’s countries. (B) World collaboration map. (C) Author collaboration network.

3.3. Citation analysis Figure 4A highlights the most cited countries, with China again at the forefront with 1588 citations, followed by the USA with 1298, and Spain with 1090. These high citation counts reflect the global impact and recognition of research originating in these countries. India has a substantial presence, with 636 citations, whereas other countries, such as Brazil and Germany, also show substantial citation figures, indicating their significant contributions to advancing knowledge and technology in UAV-based spraying applications. The most global cited documents (Figure 4B) highlight the key influential papers that have shaped the field, emphasizing the ongoing evolution and innovation within this domain. The paper by Talaviya et al. (2020) on the implementation of artificial intelligence (AI) in UAV-based agrochemical applications is the most highly cited document, with 385 citations.

3.4. Most frequent words and trend topics The most frequent word analysis in bibliometric studies identifies the most commonly occurring words or terms in the titles, abstracts or keywords of the analyzed publications. This helps in uncovering the primary themes, research focus, and trends within the literature. The word cloud in Figure 4C provides a visual representation of the prevalent research themes with terms such as ‘UAV’, ‘weed control’, ‘precision agriculture’, ‘remote sensing’ and ‘deep learning’. This indicates a strong focus on

integrating advanced technologies, such as AI and remote sensing, to enhance the efficacy and precision of drone-based agricultural practices. The prominence of terms such as ‘herbicides’, ‘aerial vehicle’ and ‘antennas’ further underscores the multifaceted nature of this research, which combines agronomy, engineering, and environmental science to address modern agricultural challenges. The trend topic analysis clearly reveals the evolution of research themes related to UAV-based crop protection over time. Early studies (2017–2019) primarily focused on image processing, spraying and weed mapping, reflecting the initial technological development of UAV applications. In recent years (2021–2023), emerging topics such as deep learning, artificial intelligence and remote sensing have gained prominence, highlighting the growing integration of advanced data analytics and AI-driven approaches in precision agriculture (Figure 5).

Figure 4. (A) Most cited countries. (B) Most global cited document. (C) World cloud map.

Figure 5. Trend topic analysis of author keywords.

3.5. Co-occurrence analysis of keywords The co-occurrence analysis of keywords highlights the interconnectedness of key research terms related to the use of UAVs in spraying and crop protection applications (Figure 6). Central themes such as ‘precision agriculture’, ‘unmanned aerial vehicle’, ‘drone’ and ‘remote sensing’ are prominently

Figure 6. Co-occurrence analysis of author’s keyword in VOSviewer.

linked, indicating their critical roles and frequent co-mention in the literature. The term ‘precision agriculture’ serves as a pivotal node, connecting diverse concepts such as ‘artificial intelligence’, ‘deep learning’, ‘weed detection’ and ‘crop protection’, highlighting the integration of advanced technologies to enhance agricultural practices. The clusters around ‘unmanned aerial vehicle’ and ‘drone’ include related terms such as ‘aerial application’, ‘pesticide application’ and ‘herbicide,’ reflecting their primary applications in targeted spraying and pest management. Additionally, the prominence of terms such as ‘deep learning’ and ‘machine learning’ in the network underscores the growing importance of AI- and data-driven approaches in optimizing UAV operations and improving precision in agricultural interventions. This network map effectively captured the multidisciplinary nature of UAV research in agriculture, highlighting the convergence of engineering, computer science and agronomy to advance this innovative field.

3.6. UAVs for crop protection in agriculture The main thematic applications of UAVs in crop protection, as revealed in the literature, are agrochemical spraying and crop health monitoring.

3.6.1. Spraying Pesticide and fungicides The use of UAVs in plant protection has expanded rapidly across field, vegetable, and fruit crops due to their flexibility in terms of spraying height, speed, nozzle type, and their relatively low cost (Subramanian et al., 2021). Studies comparing UAVs with traditional sprayers (knapsack and tractormounted) show clear advantages. For example, the N-3 UAV achieved over 20% reduction in pesticide use while improving the control efficiency for rice plant hopper and leaf roller compared to conventional methods (Xue et al., 2013). Wang et al. (2019) reported that UAVs provided pest control efficiency comparable to that of electric air pressure (EAP) knapsack sprayers at higher spray volumes, though the efficiency decreased with reduced volume, a trend also observed in rice and pepper (Wang et al., 2019; Xiao et al., 2020). Factors such as crop growth stage, canopy structure, and leaf area index further

Table 2. Application of UAVs for spraying of agrochemicals for crop protection. Crop Disease Pepper

Platform

Disease/insect

Agrochemical

Reference

Phytophthora blight

72% Cymoxanil-Mancozeb (WP)

Xiao et al. (2020)

Powdery mildew Rice blast Rust and brown eye spot Aphids

Tebuconazole (SC) 9% Pyraclostrobin (SC) Cyproconazole (SC), Azoxystrobib (SC) 20% Flonicamid (SC)

Wang et al. (2019) Wang et al. (2020) Vitória et al. (2023) Xiao et al. (2020)

Wheat Cotton

DJI T16 UAV sprayer 3WQF120-12 single rotor UAV TXA four-rotor UAV AGRAS MG-1P (DJI) DJI T16 UAV sprayer 3WQF120-12 single rotor UAV Jifei P20 UAV

Aphids Aphids and Spider Mites

Wang et al. (2019) Lou et al. (2018)

Rice Rice

TXA four-rotor UAV HyB-15L UAV

Imidacloprid (SC) & Lambda cyhalothrin (EW) 20% Acetamiprid (WP) 5% Avermectin (EC) Chlorantraniliprole (WDG) Chlorpyrifos (EC)

Wheat Rice Coffee Pepper

Rice leaf roller plant hoppers

Wang et al. (2020) Qin et al. (2016)

influence spray performance. Importantly, UAVs have been shown to maintain effective pest and disease control even at reduced pesticide doses, contributing to lower agrochemical use and environmental protection (Xiao et al., 2019). Key studies on UAV-based pest and disease management are summarized in Table 2. Herbicide/weedicide Weeds compete with crops for resources such as water, nutrients and space, causing significant yield losses in onion, garlic (30%–60%) (Siddhu et al., 2018; Tripathy et al., 2013), rice (10%–100%), wheat (10%–60%) and potato (20%–30%) (Gharde & Singh, 2018). Herbicides remain the primary method of weed control, and agri-drones offer a practical option for both pre- and post-emergence spraying under diverse field conditions. Chen et al. (2019) reported that UAV-applied pre-emergence herbicides caused no crop injury and provided 98%–100% weed control in humid, smooth soils, whereas post-emergence sprays resulted in 10%–20% crop injury and lower control efficiency (10%–70%). In comparison, knapsack sprayers performed better for post-emergence applications. Several studies have optimized UAV spraying parameters, including droplet size, spray volume, nozzle type and flight speed (Hunter et al., 2020; Shan et al., 2021). Hiremath et al. (2024) also found that, among knapsack, boom and UAV sprayers in soybean, the knapsack sprayer was most effective for weed management. Nutrient/bio-stimulants UAVs are increasingly used for foliar nutrient application, enabling rapid nutrient absorption and improving efficiency over soil application. UAV spraying with a 2% TNAU pulse wonder at 50 L/ha in green grams enhanced crop quality and yield compared to manual application (Dayana et al., 2022). Similarly, Kaniska et al. (2022) reported higher yields when NPK, micronutrients and humic acid were applied using a fuel-operated UAV at 30 L/acre. UAVs have also shown promise in grain biofortification; two UAV sprays of chelated Zn in rice produced Zn levels comparable to three manual $ZnNO_3$ sprays (Xu et al., 2021). As a low-volume method with high nutrient recovery and low residue risk, UAV foliar spraying is considered an efficient, eco-friendly option for nutrient delivery and biofortification.

3.6.2. Crop health monitoring of crops using UAVs UAVs are increasingly used for remote sensing and aerial crop monitoring, providing farmers with highresolution infrared and visual imagery to detect diseases, pests, weed emergence and other stresses (Table 3). Compared to satellite imagery, UAVs capture clearer, more detailed images because of their low-altitude and slow-flight operation. A wide range of sensors, including RGB, multispectral, hyperspectral, thermal and depth cameras are used depending on the monitoring objective (Neupane & Baysal-Gurel, 2021). Hyperspectral imaging can be used to differentiate the spectral signatures of various weed species (Huang et al., 2018). UAV-based sensing plays a key role in precision agriculture, enabling early detection of pests, diseases, weeds and abiotic stresses, allowing timely intervention. However, accurate

image interpretation and automated analysis of large datasets remain major challenges. Several UAV-based systems have been

Table 3. Crop health monitoring using UAV. Crop Platform Disease and pest monitoring Olive and DJI Phantom 3 Advanced UAV with 3-axis 1080p full HD date palm video camera

Olive Quick Decline Syndrome caused by Xylella fastidiosa

Potato

Presence of the ‘red palm weevil Detection of potato beetle damage

Grape Radish Soybean Grape Cotton Tea Rice

‘Spreading Wings’ S800 hexacopter (DJI) With sensor of sixchannel Mini Multi Camera Array Long range DT-18 coupled with DT-5Bands imaging instrument having MicaSense RedEdgeTM sensor (Phantom 4, DJI co., Ltd.), equipped with an RGB camera (12 mega pixels) DJI Phantom 3 multi-rotor Mikrokopter OktoXL (HiSystems GmbH) equipped with a nadir-facing Tetracam ADC-lite camera Eight-rotor oktokopter (HiSystems GmbH) and multispectral TetraCam ADC camera DJI Matrice 600 pro with MicaSense RedEdge-M sensor

DJI inspire 2 Quad rotor UAV with a Sentera Multispectral Double 4 K sensor Plant stress monitoring Wheat DJI S1000 with Sony NEX-7 RGB camera Grapes ARF OktoXL 6S12 (HiSystems GmbH) with thermal infrared camera and multispectral digital camera Maize hexa-copter UAV with FLIR Vue Pro R 640 thermal camera Maize six-rotor unmanned aircraft DJI S900 with RGB, Thermal and multispectral camera

Purpose

Reference Psirofonia et al. (2017)

Hunt & Rondon (2017)

Detection of Flavescence dorée Grapevine Disease Fusarium wilt of radish

Albetis et al. (2017)

Soybean Foliar Diseases Grapevine leaf stripe disease

Tetila et al. (2017) Di Gennaro et al. (2016) Xavier et al. (2019)

Ramularia Leaf Blight Cotton Disease

Ha et al. (2017)

Monitoring Thosea sinensis Walker in Tea Plantations Monitoring narrow brown leaf spot severity

Yuan et al. (2023)

Drought Assessment Water Stress Assessment

Su et al. (2020) Zúñiga Espinoza et al. (2017) Zhang et al. (2019) Zhang et al. (2023)

Canopy Temperature Soil moisture content

Gu et al. (2023)

developed for specific applications. For example, AggieAir integrates RGB, NIR, and thermal sensors to estimate crop nitrogen, chlorophyll and soil moisture levels (Hassan-Esfahani et al., 2015). Thermal sensors have been used to assess grapevine water status via the Crop Water Stress Index (Santesteban et al., 2017). Multispectral UAV imaging combined with CNN-based machine learning has enabled effective monitoring of yellow rust in wheat (Su et al., 2020). UAV-mounted cameras have also been used to detect red palm weevil infestation in date palms (Psirofonia et al., 2017). In addition to crop health monitoring, UAVs support weed mapping (Huang et al., 2018; Lottes et al., 2017) and yield prediction (Mathivanan & Jayagopal, 2022). UAV-based multispectral imaging has also shown strong potential for assessing crop productivity. For example, a recent study demonstrated that vegetation indices derived from UAV multispectral imagery, combined with machine learning algorithms such as random forest and support vector machines, can accurately predict onion bulb yield across different planting dates and growth stages (Wayal et al., 2026). Recent advances in machine

learning and deep learning have further enhanced the capability of UAVbased remote sensing by enabling efficient analysis and fusion of large and complex datasets. Emerging approaches such as foundation models and interpretable deep learning networks are increasingly being applied to hyperspectral and multimodal agricultural data. For instance, SpectralGPT, a spectral remote sensing foundation model, enables generalized feature learning across diverse spectral datasets, improving the robustness of crop monitoring applications (Hong et al., 2024). Similarly, LRR-Net (low-rank representation network) has been developed for interpretable hyperspectral anomaly detection, facilitating the identification of subtle crop stress signals (Li et al., 2024), while RustQNet, a multimodal deep learning framework, integrates spectral and visual information for the quantitative assessment of wheat stripe rust severity (Deng et al., 2024). These advances highlight the growing integration of artificial intelligence with UAV-based sensing systems, enabling more accurate, automated, and scalable crop health monitoring in precision agriculture. Key studies are summarized in Table 3. The availability of benchmark datasets plays a critical role in the development and evaluation of object detection models for UAV-based crop protection. Several publicly available datasets have been developed to support research on pest detection, disease identification and weed mapping using aerial imagery. These datasets typically include annotated RGB or multispectral UAV images and are widely used to train and benchmark deep learning models for agricultural applications. A summary of representative UAV-based datasets used for crop monitoring and protection is presented in Table 4.

Table 4. Representative datasets used for UAV-based object detection in crop protection. Dataset PlantVillage DeepWeeds WeedMap Agriculture-Vision PestNet Deep Object Detection of Crop Weeds

Application Plant disease detection Weed detection Weed mapping Crop stress detection Insect pest detection Weed detection

Data type RGB images

Key features Large annotated dataset of crop diseases

RGB images UAV RGB imagery Aerial imagery RGB images

Dataset for weed classification using deep learning Pixel-level weed annotation in agricultural fields

Reference Singh & Gahlawat (2025) Olsen et al. (2019) Sa et al. (2018)

Large-scale aerial dataset for agricultural field analysis

Chiu et al. (2020)

Large insect pest dataset for crop protection research

Liu et al. (2019)

RGB images

more than 3000 RGB images of chicory plantations, collected using a UAV system at various stages of crop and weed growth

Gallo et al. (2023)

Figure 7. Factors to be considered while drone spraying.

3.6.3. Factors affecting the efficiency of agrochemical spray using UAV The bibliometric analysis of the retrieved documents highlights that factors such as flight height, flight speed, nozzle type, spray volume and spray mixture significantly influence the efficiency and precision of agrochemical spray using UAVs (Figure 7). These parameters are critical because they directly affect the resulting droplet size, density, drift and coverage. Consequently, optimizing or standardizing these variables for different crops and conditions is essential to achieve high efficiency and precision. The subsequent sections synthesize the literature focusing on these parameters, providing necessary guidelines for researchers, farmers and service providers to develop standard operating procedures (SOPs) for various UAV models and crops. Flight height and velocity Operational height and speed are critical factors influencing droplet deposition and uniformity in UAVbased agrochemical applications. In rice, optimal deposition was achieved at a height of 1.5 m and a speed of 5 m/s speed using a HyB-15L UAV (Qin et al., 2016). For cotton, effective defoliation occurred at 1.5 m with flight speeds of 3.12, 2.51

and 3.76 m/s for four-, six- and eight-rotor drones, respectively (Liao et al., 2019), while Lou et al. (2018) reported 2 m as the ideal height using a Jifei P20 UAV. A hexacopter study also reported that a depth of 1.5 m to provide the best spray uniformity (Hussain et al., 2019). For weed control with a single-rotor drone, maximum deposition was obtained at a height of 2 m and a speed of 2 m/s (Ahmad et al., 2020). Infrared thermal imaging studies have shown that increasing the flight speed reduces the droplet density, coverage and size (Lv et al., 2019). In sugarcane, a height of 3 m and a speed of 4 m/s ensure better deposition across canopy layers (Zhang et al., 2020). Similar evaluations have been conducted in peach orchards (Li et al., 2022; Meng et al., 2020), coffee plantations (Souza et al., 2022), and vineyards

(Biglia et al., 2022) to develop crop-specific SOPs. Thus, users must standardize flight height and speed based on crop characteristics, wind conditions and UAV type. Spray volume and nozzle Nozzle type, spray volume and liquid pressure are crucial determinants of droplet deposition and overall pesticide application efficiency in UAV spraying. Studies have shown that lower spray volumes with larger droplets enhance deposition (Fritz et al., 2006). Various nozzle types and sizes have been evaluated for their effects on droplet penetration, uniformity, drift and coverage (Derksen et al., 2008; Ferguson et al., 2016; Kirk, 2007; Zhu et al., 2006). Proper nozzle selection can significantly improve canopy penetration while reducing drift (Wolf & Daggupati, 2009). Owing to the limited number of drone-specific nozzles, flat-fan nozzles are widely used (He et al., 2018). Centrifugal nozzles (200–800 mL/min) are effective for aphid management in cotton (Lou et al., 2018). The spray volume strongly influences droplet deposition; in wheat, UAV deposition is comparable to that of knapsack sprayers when using > 16.8 L/ha and coarse nozzles (Wang et al., 2019). In vineyards, higher flight speeds improved deposition with conventional nozzles (Biglia et al., 2022). In rice, hydraulic nozzles showed higher droplet density, which is further enhanced by the use of adjuvants (Chen et al., 2020). Twin flat nozzles also produced greater deposition than single flat nozzles (Chojnacki & Pachuta, 2021). The cone and flat-fan nozzles showed maximum discharges of 646 and 827 mL/min, respectively (Kailashkumar et al., 2023). Spray drift remains a major concern in UAV applications. Wind-tunnel tests revealed that centrifugal nozzles pose higher drift risk than hydraulic nozzles, while adjuvants help reduce drift risk (Wang et al., 2020). Therefore, developing accurate drift prediction models is essential for safe UAV spraying. Pesticide formulation and adjuvants Although UAV use in agriculture is expanding rapidly, challenges such as droplet drift, pesticide bounceoff, and environmental risks persist. Recent studies highlight spray adjuvants as an effective strategy to improve deposition and reduce drift. Wang et al. (2018) reported substantial drift reduction with various adjuvants, such as Silwet DRS-60 (65%), ASFA + B (62%), T1602 (59%), Break-thru Vibrant (46%), QF-LY (42%) and Tmax (19%), compared to water. Adjuvants have also improved spray performance at reduced pesticide doses, such as a 20% dose reduction for aphid control in wheat (Meng et al., 2018). Vegetable oil enhanced droplet coverage (Xiao et al., 2019), while a novel oil-in-water microemulsion of thiamethoxam and acetamiprid improved wettability and deposition (Song et al., 2020). Methylated vegetable oil increased the efficacy of prothioconazole against Fusarium head blight (Yan et al., 2021). In citrus canopies, tank-mix adjuvants increased droplet coverage and reduced leaf bounce using DJI T20 and T30 drones (Meng et al., 2022). Liu et al. (2023) demonstrated that both the nozzle type and the adjuvant strongly influence drift: SDS reduced drift by 69.2% (XR nozzle) and 66.3% (TXVK), while silicone adjuvant achieved a 78% reduction with the AIXR nozzle. However, some studies, such as Wang et al. (2022), reported no significant improvement in droplet deposition, though pest and disease control was still enhanced. Overall, adjuvants play a key role in improving UAV spray effectiveness and minimizing drift. Droplet size, density, coverage and penetration Droplet size and deposition are critical parameters in UAV-based agrochemical spraying. Key metrics include droplet density (number of droplets per unit area), deposition coverage (percentage of area covered by droplets) and arithmetic mean droplet size (Cunha et al., 2012; Subramanian et al., 2021). Deposition coverage is particularly important for evaluating spray efficiency. Studies have shown that UAV flight parameters strongly influence deposition. In rice, higher flight speed and height reduce droplet deposition, and wind direction and speed were identified as important considerations (Chen et al., 2016). Compared with UAVs, knapsack sprayers produce nearly double the droplet coverage, largely because of their higher spray volumes (250–300 L/ha vs. 15–20 L/ha for UAVs) (Xiao et al., 2020). Increased plant height and leaf area indices also reduced coverage in the lower canopy layers. Droplet size significantly affects deposition, penetration and drift. Larger droplets resulted in higher deposition, better canopy penetration, and lower drift, while very small

droplets (<160 µm VMD) increased the drift risk. A 10 m buffer zone was recommended to minimize off-target movement (Chen et al., 2020). Droplet density increases with spray volume and is typically higher in the upper canopy than in the lower canopy (Xiao et al., 2020). Knapsack

sprayers also generate twice the droplet density of UAVs, again reflecting differences in spray volume. Uniform droplet distribution across upper, middle, and lower canopy layers remains a major challenge in UAV spraying, making it less consistent than conventional knapsack sprayers for uniform disease control. Economic viability Several studies have examined the economic rationale for adopting UAV technology in agriculture. Ramteke et al. (2025) reported significant savings in labour and pesticide use with UAV spraying. In China, UAV adoption increased revenue by $434–488 per hectare and reduced labour time by 14.4–15.8 h per hectare (Quan et al., 2023). Despite these benefits, high initial investment, high technical training requirements, and maintenance challenges remain key barriers (Ivezi et al., 2023). Although many researchers acknowledge the substantial upfront cost, they argue that long-term gains – particularly reduced labour and pesticide expenses often outweigh these initial expenditures (Huang et al., 2018), with some studies even indicating quick returns on investment (Safaeinezhad et al., 2025). Comparisons between UAV-based and traditional spraying methods commonly show that UAVs become more cost-effective over time because of their lower chemical use and labour requirements (Umeda et al., 2022). However, concerns persist regarding affordability for small-scale farmers, for whom the initial investment and maintenance costs may be prohibitive (Pathak et al., 2020). Differences in labour cost structures and farm size also contribute to inconsistent cost−efficiency assessments across studies. The lack of comprehensive economic data across diverse regions and production scales highlights the need for long-term, standardized cost evaluations to accurately compare UAV-based and conventional agricultural practices.

3.6.4. Advantages and disadvantages of UAVs in crop protection UAVs offer numerous advantages in crop protection, particularly in precision agriculture. The ability of these methods to provide real-time data enables farmers to accurately monitor crop health, allowing timely intervention. This technology is cost-effective, as it reduces the need for manual labour and minimizes the use of inputs such as water, fertilizers and pesticides, leading to significant savings. In addition, UAVs contribute to environmental benefits by ensuring that resources are used efficiently, thus reducing waste and environmental impacts. Owing to their high efficiency and accuracy in covering large fields, UAVs are invaluable for modern farming practices (Figure 8). However, the use of UAVs for agriculture has several limitations. Operating agricultural UAVs requires special knowledge and skills, which poses a technical challenge for many farmers. These UAVs often have limited battery life, which restricts the duration and extent of their use. Many UAVs lack advanced features of collision avoidance and auto navigation that can limit their functionality in diverse farming scenarios. Regulatory issues such as the need for government registration and compliance with airspace regulations add another layer of complexity. UAVs are weather-sensitive and may not perform well under certain

Figure 8. Pros and cons of drone application in crop protection.

conditions. Additionally, their effectiveness may be limited for specific crops and problems, and there are concerns about privacy, as UAVs capture detailed images of private land.

- Discussion The bibliometric analysis reveals a growing interest in agricultural research, particularly in areas such as remote sensing and precision agriculture. The increase in publications around 2020 could be linked to advancements in technology and the need for sustainable agricultural practices. The increase in publications, indicates a growing interest and investment in research related to agriculture and crop protection. This trend may be driven by the need for sustainable agricultural practices and the integration of technology in farming (Anam et al., 2024). The dominance of Chinese institutions in research output underscores China's investment in agricultural sciences. The leading role of Chinese institutions, such as ‘China Agricultural University’ and ‘South China Agricultural University’, highlights China's significant investment in agricultural research. This is consistent with China's strategic focus on food security and agricultural modernization, including massive government funding supporting UAV innovation and

agricultural mechanization (Wang et al., 2023). The variety of journals and international authors indicates a multidisciplinary approach to addressing agricultural challenges. The prominence of ‘Remote Sensing’ and ‘Agronomy’ as the most relevant sources suggests a strong focus on technological applications and agricultural sciences. Remote sensing technologies are increasingly used for precision agriculture, which aligns with the global trend towards data-driven farming practices (López-Granados et al., 2020). The analysis reveals that China and the USA are the leading contributors to research in this field, both in terms of publication volume and citation impact. Similar results were reported by Singh et al. (2022), where USA and China were leading contributors to the research output of the use of UAV in precision agriculture. The high level of international collaboration, as indicated by the MCP and SCP, suggests a global effort to address agricultural challenges. The USA’s high MCP and citation impact suggest strong international partnerships, particularly in areas such as precision agriculture and robotics. The most cited documents and the word cloud emphasize the importance of advanced technologies such as remote sensing, deep learning, and computer vision in modern agriculture. These insights reflect the field's focus on leveraging technology to improve agricultural efficiency and sustainability. The focus on ‘agricultural robots’ and ‘herbicide application’ signals a shift toward automation to address labour shortages and environmental concerns. Research on AI-driven decision systems (Gupta et al., 2020) is likely to grow, as evidenced by the rapid citation of recent papers. The active participation of various countries and the high citation counts indicate a vibrant and impactful research community. The co-occurrence analysis reveals a strong emphasis on integrating advanced technologies such as AI, machine learning, and remote sensing into agricultural practices. The prominence of precision agriculture and site-specific management techniques indicates a shift towards more efficient and sustainable farming methods. The prominence of ‘artificial intelligence’, ‘machine learning’ and ‘deep learning’ reflects a paradigm shift toward data-driven decision-making in agriculture. AI applications, such as weed detection and crop health monitoring, are increasingly used to optimize resource use and reduce environmental impacts (Kamilaris & Prenafeta-Boldú, 2018). For example, AI-powered UAVs enable real-time weed mapping, reducing herbicide overuse (Lottes et al., 2017). The focus on weed management and herbicide application highlights the ongoing challenges in crop protection and the need for innovative solutions. Terms such as ‘weed detection’, ‘weed mapping’ and ‘site-specific weed management’ emphasize efforts to minimize herbicide use through targeted interventions. This aligns with global trends toward sustainable agriculture, where precision technologies reduce chemical runoff and environmental harm (Getahun et al., 2024). The interconnectedness of these themes suggests a multidisciplinary approach, where technology, environmental science, and agronomy converge to address complex agricultural issues. The use of UAVs for tasks such as aerial spraying and weed mapping demonstrates the practical application of these technologies in the field. UAVs are widely adopted for tasks such as aerial imaging, pesticide application, and normalized difference vegetation index (NDVI)-based crop monitoring, enhancing efficiency in large-scale farming (Zhang & Kovacs, 2012). Their integration with computer vision (e.g. weed detection) supports sitespecific management, a cornerstone of precision agriculture (Torres-Sánchez et al., 2015). Overall, the analysis underscores the transformative impact of technology on agriculture, driving advancements in

precision farming, sustainable practices and efficient resource management. The research community is actively exploring ways to leverage these technologies for crop protection to enhance productivity while minimizing environmental impacts. Despite the rapid advancement of UAV-based crop protection technologies, several challenges still limit their large-scale practical deployment. One of the major constraints is the limited availability of high-quality, annotated datasets for training robust machine learning and deep learning models, which often affects model generalization across crops, environments and growing seasons (Huang et al., 2025; Joshi et al., 2023). In addition, real-time processing of large volumes of UAV imagery and the integration of data from multiple sensors (e.g. RGB, multispectral, hyperspectral and thermal) remain significant technical challenges (Zhang & Zhu, 2023). Future research should therefore focus on developing standardized datasets,

improving cross-sensor data fusion techniques, and designing lightweight, real-time analytics frameworks that can support scalable and operational UAV-based crop protection systems.

- Conclusion In conclusion, this study has examined the escalating use of UAVs for crop protection. Bibliometric and cooccurrence analyses reveal that this field is experiencing rapid growth with substantial contributions tracing from China and the USA, which dominate both publication output and citation metrics. This research heavily focuses on integrating advanced technologies, such as AI and remote sensing, into precision agriculture, as evidenced by co-occurrence analysis. Despite encouraging advancements, few studies have critically addressed the practical challenges encountered while implementing these technologies across diverse agricultural landscapes. Overall, this investigation delineates a dynamic and interdisciplinary research landscape that fosters driving innovations in agricultural technology and sustainable farming practices, which is particularly applicable in developing agrarian countries. To optimize the application of agrochemicals via UAVs, careful consideration must be given to spray parameters such as spray velocity, height, nozzle type, spray volume, and spray mixture tailored to specific crops, purposes and environmental conditions. The advantages of UAV spraying, such as enhanced access to challenging terrains, reduced human exposure to pesticides, decreased chemical usage, and labour and time savings, highlight its potential benefits. However, it is essential to carefully assess and mitigate agrochemical drift by selecting appropriate nozzles and adjuvants. Additionally, rigorous assessment of pesticide efficacy is necessary to determine the optimal dosage and application frequency. Future research directions should prioritize the development of sustainable custom hiring models for UAV usage and establish frameworks for effective data sharing to support the maintenance of machine learning and deep learning models. Notably absent from the current discourse are specific bibliometric analyses pertinent to these areas, which could serve as critical dimensions for future studies. Key recommendations for further exploration include investigating targeted efficacy trials focused on optimizing pesticide dosage and frequency for UAV applications that conduct life cycle assessments on UAV-based agricultural applications to inform sustainable custom hiring strategies, developing comprehensive frameworks for UAV data sharing aimed at preserving and enhancing machine learning and deep learning models for applications such as yield prediction and stress characterization. There are limited data on the long-term environmental impacts of UAV-sprayed chemicals, particularly concerning their effects on beneficial insects and soil health. Addressing these gaps will not only enrich the understanding of UAV technologies in agriculture but also facilitate the successful implementation of these innovations in varied agricultural contexts.

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RESEARCH ARTICLE

Advancements and trends in UAV utilization for crop protection: a bibliometric analysis Rajiv B. Kalea , Kiran Khandagalea , Bhushan Bibwea, Bhaskar Gaikwadb, Rohini Bhata, Suresh J. Gawandea and Vijay Mahajana a

ICAR-Directorate of Onion and Garlic Research, Pune, India; bICAR-National Institute of Abiotic Stress Management, Baramati, India ABSTRACT

ARTICLE HISTORY

Unmanned aerial vehicles (UAVs), or drones, have become pivotal tools in precision agriculture, particularly for aerial spraying and crop health monitoring. Their adoption addresses farmers' health issues related to manual pesticide exposure and ensures the timely execution of crop protection activities. This paper presents a systematic investigation and comprehensive bibliometric analysis of the scientific literature on UAV utilization in crop protection, spanning from 2007 to 2024. Using Scopus data analyzed with Bibliometrix and VOSviewer, the study identified 439 relevant documents to reveal key research trends and influential collaboration networks. The analysis confirms a marked increase in research output, with China and the USA leading globally in terms of publication volume and citation impact. Core research themes centre on integrating advanced technologies, such as remote sensing, deep learning and artificial intelligence, to enhance the precision of applications. The findings underscore the potential of UAVs as an efficient, safer, and more sustainable alternative to conventional methods. However, challenges specific to the Indian agricultural context, such as small landholdings and high initial costs, are highlighted, offering valuable insights for other developing agrarian economies.

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Agrochemical spray; bibliometrics; crop protection; sustainability in agriculture; UAV

Introduction The agricultural sector remains the backbone of the Indian economy, accounting for more than 60% of employment. To meet the demands of a rapidly increasing global population, which is projected to reach approximately 10 billion by 2050 (Dutta & Goswami, 2020). The enhancement of agricultural productivity and efficiency is imperative to ensure worldwide food security (Hunter et al., 2017). Consequently, precision agriculture (PA) is gaining significant attention, utilizing cutting-edge technologies for data collection, analysis and communication to implement customized crop management strategies. These practices aim to optimize

crop yield, minimize the wastage water and nutrients to mitigate adverse environmental impacts (Boursianis et al., 2020; Sishodia et al., 2020). In this context, UAV-based crop protection represents a transformative approach for modern agriculture by enabling precise, timely and site-specific agrochemical applications. This technology not only improves spraying efficiency and reduces chemical wastage but also minimizes the occupational exposure of farmers to hazardous pesticides, thereby enhancing environmental sustainability and human health safety. Consequently, understanding the global research landscape and technological trends in UAV-enabled crop protection is essential for guiding future innovations, policy formulation, and large-scale adoption, particularly in developing agrarian economies. Despite the potential of PA, farmers in India largely use conventional methods for seed planting, composting and pesticide application. These traditional techniques are often time-consuming and less effective, particularly for chemical spraying (Rolle et al., 2015). Furthermore, the manual application of pesticides exposes farmers to health issues such as tumors, allergies and hypersensitivity (Damalas & Koutroubas, 2016). Globally, pests, diseases and weeds are estimated to cause 20%–40% losses in major food crops annually, resulting in economic losses exceeding USD 220 billion due to plant diseases and approximately USD 70 billion due to invasive insects CONTACT Rajiv B. Kale

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(Junaid & Gokce, 2024). At the same time, conventional pesticide spraying methods often suffer from low application efficiency, with nearly 30%–50% of agrochemicals lost due to spray drift and off-target deposition. In contrast, UAV-based spraying systems can improve application precision, reduce chemical use by 15%–30%, highlighting their growing importance in sustainable crop protection. The challenges faced by conventional farmers were exacerbated by the COVID-19 pandemic, highlighting the urgent need for technological advancement in crop management (Varshney et al., 2020). Unmanned aerial vehicles (UAVs), also known as drones, have emerged as pivotal tools to address these issues (Hafeez et al., 2023). They are now extensively used in agriculture for tasks such as crop monitoring, estimating crop yield and agrochemical applications (Anthony et al., 2014; Bendig et al., 2012; Hiremath et al., 2024). Drones are expected to become an important component of Agriculture 4.0 by supporting the integration of the IoT, big data, artificial intelligence and robotics across agricultural production and supply chains. The scientific literature on the use of UAVs in crop protection has significantly increased over the last decade, necessitating quantitative review methods to understand the knowledge structures and research trends in this emerging field. Prior studies have provided general bibliometric reviews on the use of UAVs in agriculture and forestry (Raparelli & Bajocco, 2019; Rejeb et al., 2022). A focused and comprehensive bibliometric analysis concentrating specifically on the advancements and trends in UAV utilization for crop protection, particularly for agrochemical spraying, remains underexplored. This study distinguishes itself by systematically analyzing literature spanning from 2007 to 2024 to map the intellectual structure, influential contributors and key thematic clusters related solely to UAV-based crop protection. The novelty lies in its detailed synthesis of crucial application parameters such as flight height, nozzle type, and pesticide formulation and its explicit discussion of the opportunities and adoption challenges in the Indian context. The aim of the present study is to provide a systematic and comprehensive bibliometric analysis of the global scientific output concerning the application of UAVs in crop protection and spraying. The objectives are to: (1) map key research trends, influential authors, and collaborative networks using quantitative bibliometric tools; (2) synthesize the thematic literature on the optimization factors for UAV spraying and crop monitoring; and (3) highlight the opportunities and challenges specific to the Indian agricultural context, offering valuable perspectives for other developing agrarian economies.

- Methodology 2.1. Retrieval of data Scopus, a leading database for scientific literature, was used for comprehensive bibliometric analysis. This study focused on identifying the literature concerning the use of

UAVs for crop protection and spraying. Boolean operators ‘AND’ and ‘OR’ were employed to create a comprehensive advanced search setup in Scopus. The search strategy for data retrieval from Scopus was as follows: (TITLE-ABS-KEY (‘drone’) OR TITLE-ABS-KEY (‘unmanned aerial vehicle’) OR TITLE-ABS-KEY (‘UAV’) OR TITLE-ABS-KEY (‘unmanned aircraft system’) OR TITLE-ABS-KEY (‘remotely piloted aircraft’) AND TITLE-ABS-KEY (‘crop protection’ OR ‘herbicide spraying’ OR ‘herbicide’ OR ‘fungicide’ OR ‘biostimulant’ OR ‘pesticide spray’)). A total of 489 documents, spanning from 2007 to 2024, were retrieved and exported from Scopus in the CSV format for further analysis.

2.2. Screening of data This study employed a bibliometric analysis approach to examine research focused on UAV use for agricultural spraying and crop protection. This investigation followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. The retrieved articles in the CSV file were screened to remove duplicates and irrelevant literature. Documents that were non-English, not peer-reviewed, non-academic, or not focused on UAV spraying/crop protection were excluded from the dataset (Figure 1 and Table 1).

2.3. Bibliometric analysis The cleaned data were then analysed using Bibliometrix R package using its web-interface tool Biblioshiny (Aria & Cuccurullo, 2017) and VOSviewer version 1.6.20 (Van Eck & Waltman, 2010), both renowned for their

Figure 1. PRISMA flow diagram illustrating the study selection process for the bibliometric study.

Table 1. The features of dataset used in present analysis. Dataset features Document contents Timespan Documents Annual growth rate % Document average age Average citations per doc Document contents Keywords plus (ID) Author's keywords (DE) Authorship details Authors Authors of single-authored docs Authors collaboration Single-authored docs Co-authors per doc International co-authorships %

2007:2024 439 25.1 3.4 20.24 2343 1373 1680 14 14 4.91 25.13

user-friendly interface and clear visual representation in bibliometric studies. The data were analyzed for various parameters, such as annual publication output, influential authors, journal citations, intercountry collaboration, keyword’s co-occurrence analysis, etc.

2.3.1. Publication trends and relevant sources, affiliations and authors Annual publication output: The number of documents published per year was quantified to identify growth trajectories and publication trends in the use of UAVs for crop protection. Influential contributors and sources: this analysis was performed to identify the ‘most relevant authors’ where authors were ranked by the highest total number of publications; ‘most relevant affiliations’ institutions were identified by the

highest count of documents, and the ‘most relevant sources’ here journals were ranked by their contribution volume to the dataset.

2.3.2. Corresponding author countries, most cited countries and most cited documents To assess the global landscape of research and its impact, the following analyses were conducted. ‘Corresponding author countries and collaboration’: the documents were categorized based on the country of the corresponding author. A distinction was made between Single-Country Publications (SCP) and MultiCountry Publications (MCP) to map the extent of international collaboration in the field. ‘Most cited countries’: countries were ranked by the total number of citations received by their publications to quantify their global research influence. ‘Most globally cited documents’: a list of the most highly cited individual research papers was generated to identify key influential documents that have significantly shaped the field. 2.3.3. Word cloud map, trend topics and co-occurrence analysis of keywords ‘Word cloud map’: a word frequency analysis was performed on the titles, abstracts, and author keywords of the dataset. The most commonly occurring terms were visualized in a word cloud map to provide a visual representation of the prevalent research themes and focus areas within the literature. Trend topics analysis was conducted to explore the temporal evolution of key research themes in UAV-based crop protection. Author keywords extracted from the Scopus dataset were analyzed using the

Bibliometrix package in R (Aria & Cuccurullo, 2017). Keyword frequencies were calculated and mapped across different time intervals. Keyword co-occurrence analysis was employed to identify and visualize the key thematic clusters and intellectual structure of the research field. This analysis was executed using VOSviewer (v1.6.20), a tool specifically designed for constructing and visualizing bibliometric maps. From the total pool of 1375 keywords identified in the dataset, a selection was made based on a minimum frequency criterion. Only the 37 keywords that appeared a minimum of seven times in the document set were used for the analysis.

- Results The present section provides bibliometric analysis of data retrieved from the Scopus regarding the adoption of UAVs in crop protection. A total of 439 documents were remained after screening and processing and were used for further bibliometric analysis. These documents were comprised of articles (287), book chapters (15), conference papers (102), reviews (28), conference reviews, data papers, notes and short surveys, among others.

3.1. Publication growth and relevant sources, affiliations, and authors Figure 2 reveals the significant trends and key contributors to this emerging field. Figure 2A demonstrates a multi-fold increase in annual scientific production from only one publication in 2007 to 90 publications in 2023, with an annual growth rate of over 25%, highlighting the growing academic interest and research output in the use of UAVs for crop protection. Figure 2B highlights the most relevant sources from which this research is being published. These 439 documents were published in more than 200 journals. The leading journals are Remote Sensing, Agronomy and Pest Management Science, with 20, 19 and 18 documents, respectively, indicating a strong intersection between UAV technology and precision agriculture. The diversity sources like Computers and Electronics in Agriculture, Remote Sensing, Crop Protection reflects the interdisciplinary nature of this research, integrating insights from plant science, engineering and environmental studies to develop comprehensive UAV-based spraying solutions. The institutional/affiliation analysis in Figure 2C reveals that China Agricultural University is the most prolific, with 76 publications. Other notable institutions include South China Agricultural University and North Carolina State University, which point to a strong academic focus on integrating UAV technology into agricultural practices. With five Chinese institutions ranking in the top ten affiliations, the bibliometric data clearly indicates the substantial research output and dedicated focus of China on advancing UAVs in crop protection. Tamil Nadu

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Figure 2. (A) Annual scientific production. (B) Most relevant sources. (C) Most relevant affiliations. (D) Most relevant authors.

Agricultural University from India also features among the top ten most prolific affiliations in this research domain. Finally, the most relevant authors are shown in Figure 2D, indicating that Lan Y is the most relevant author, with 18 publications, followed by Xue X, with 11 papers. Both of these authors are from China, further emphasizing China's leadership in this research domain. Researchers from 58 countries have studied the UAVs in crop protection. Among these, China, the USA and India are the top three countries in terms of publication output.

3.2. Corresponding author countries and international collaboration The present bibliometric analysis offers a comprehensive overview of the global research landscape on UAV-based spraying, highlighting the distribution of corresponding authors by country, the most influential countries in terms of citations, the top-cited publications, and the dominant research themes within this field. Figure 3A reveals that China leads significantly in the number of publications, both in single-country publications (SCP) and multi-country publications (MCP), underscoring its dominant role in this research field. The USA is the second most prolific nation, also exhibiting high output in both categories. India and Brazil also contributed notably, although their MCP contributions were comparatively lower, suggesting a greater emphasis on domestically focused research efforts within their respective agricultural contexts. More than 25% of the articles are MCP which reflects the substantial international collaboration in this research domain. The world collaboration map clearly highlights a central, high-frequency collaboration axis between the USA and China (Figure 3B). This demonstrates that the two countries form the most robust partnership within the global scientific research network in this domain. China, which is the overall leading country in publication output, acts as a pivotal node in the network, maintaining active and frequent collaboration with numerous countries. Author co-occurrence analysis was

performed using Biblioshiny in the domain of UAVs for crop protection (Figure 3C). The major clusters (red and green) are centred around the most prolific authors, such as Lan Y, Xue X and Zhang S. This cluster reflects the strong domestic research community and high collaboration frequency, primarily among Chinese authors.

Figure 3. (A) Corresponding author's countries. (B) World collaboration map. (C) Author collaboration network.

3.3. Citation analysis Figure 4A highlights the most cited countries, with China again at the forefront with 1588 citations, followed by the USA with 1298, and Spain with 1090. These high citation counts reflect the global impact and recognition of research originating in these countries. India has a substantial presence, with 636 citations, whereas other countries, such as Brazil and Germany, also show substantial citation figures, indicating their significant contributions to advancing knowledge and technology in UAV-based spraying applications. The most global cited documents (Figure 4B) highlight the key influential papers that have shaped the field, emphasizing the ongoing evolution and innovation within this domain. The paper by Talaviya et al. (2020) on the implementation of artificial intelligence (AI) in UAV-based agrochemical applications is the most highly cited document, with 385 citations.

3.4. Most frequent words and trend topics The most frequent word analysis in bibliometric studies identifies the most commonly occurring words or terms in the titles, abstracts or keywords of the analyzed publications. This helps in uncovering the primary themes, research focus, and trends within the literature. The word cloud in Figure 4C provides a visual representation of the prevalent research themes with terms such as 'UAV', 'weed control', 'precision agriculture', 'remote sensing' and 'deep learning'. This indicates a strong focus on integrating advanced technologies, such as AI and remote sensing, to enhance the efficacy and precision of drone-based agricultural practices. The prominence of terms such as 'herbicides', 'aerial vehicle' and 'antennas' further underscores the multifaceted nature of this research, which combines agronomy, engineering, and environmental science to address modern agricultural challenges. The trend topic analysis clearly reveals the evolution of research themes related to UAV-based crop protection over time. Early studies (2017–2019) primarily focused on image processing, spraying and weed mapping, reflecting the initial technological development of UAV applications. In recent years (2021–2023), emerging topics such as deep learning, artificial intelligence and remote sensing have gained prominence, highlighting the growing integration of advanced data analytics and AI-driven approaches in precision agriculture (Figure 5).

Figure 4. (A) Most cited countries. (B) Most global cited document. (C) World cloud map.

Figure 5. Trend topic analysis of author keywords.

3.5. Co-occurrence analysis of keywords The co-occurrence analysis of keywords highlights the interconnectedness of key research terms related to the use of UAVs in spraying and crop protection applications (Figure 6). Central themes such as 'precision agriculture', 'unmanned aerial vehicle', 'drone' and 'remote sensing' are prominently

Figure 6. Co-occurrence analysis of author's keyword in VOSviewer.

linked, indicating their critical roles and frequent co-mention in the literature. The term 'precision agriculture' serves as a pivotal node, connecting diverse concepts such as 'artificial intelligence', 'deep learning', 'weed detection' and 'crop protection', highlighting the integration of advanced technologies to enhance agricultural practices. The clusters around 'unmanned aerial vehicle' and 'drone' include related terms such as 'aerial application', 'pesticide application' and 'herbicide,' reflecting their primary applications in targeted spraying and pest management. Additionally, the prominence of terms such as 'deep learning' and 'machine learning' in the network underscores the growing importance of AI- and data-driven approaches in optimizing UAV operations and improving precision in agricultural interventions. This network map effectively captured the

multidisciplinary nature of UAV research in agriculture, highlighting the convergence of engineering, computer science and agronomy to advance this innovative field.

3.6. UAVs for crop protection in agriculture The main thematic applications of UAVs in crop protection, as revealed in the literature, are agrochemical spraying and crop health monitoring.

3.6.1. Spraying Pesticide and fungicides The use of UAVs in plant protection has expanded rapidly across field, vegetable, and fruit crops due to their flexibility in terms of spraying height, speed, nozzle type, and their relatively low cost (Subramanian et al., 2021). Studies comparing UAVs with traditional sprayers (knapsack and tractormounted) show clear advantages. For example, the N-3 UAV achieved over 20% reduction in pesticide use while improving the control efficiency for rice plant hopper and leaf roller compared to conventional methods (Xue et al., 2013). Wang et al. (2019) reported that UAVs provided pest control efficiency comparable to that of electric air pressure (EAP) knapsack sprayers at higher spray volumes, though the efficiency decreased with reduced volume, a trend also observed in rice and pepper (Wang et al., 2019; Xiao et al., 2020). Factors such as crop growth stage, canopy structure, and leaf area index further

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Table 2. Application of UAVs for spraying of agrochemicals for crop protection. Crop Disease Pepper

Platform

Disease/insect

Agrochemical

Reference

Phytophthora blight

72% Cymoxanil-Mancozeb (WP)

Xiao et al. (2020)

Powdery mildew Rice blast Rust and brown eye spot Aphids

Tebuconazole (SC) 9% Pyraclostrobin (SC) Cyproconazole (SC), Azoxystrobib (SC) 20% Flonicamid (SC)

Wang et al. (2019) Wang et al. (2020) Vitória et al. (2023) Xiao et al. (2020)

Wheat Cotton

DJI T16 UAV sprayer 3WQF120-12 single rotor UAV TXA four-rotor UAV AGRAS MG-1P (DJI) DJI T16 UAV sprayer 3WQF120-12 single rotor UAV Jifei P20 UAV

Aphids Aphids and Spider Mites

Wang et al. (2019) Lou et al. (2018)

Rice Rice

TXA four-rotor UAV HyB-15L UAV

Imidacloprid (SC) & Lambda cyhalothrin (EW) 20% Acetamiprid (WP) 5% Avermectin (EC) Chlorantraniliprole (WDG) Chlorpyrifos (EC)

Wheat Rice Coffee Pepper

Rice leaf roller plant hoppers

Wang et al. (2020) Qin et al. (2016)

influence spray performance. Importantly, UAVs have been shown to maintain effective pest and disease control even at reduced pesticide doses, contributing to lower agrochemical use and environmental protection (Xiao et al., 2019). Key studies on UAV-based pest and disease management are summarized in Table 2. Herbicide/weedicide Weeds compete with crops for resources such as water, nutrients and space, causing significant yield losses in onion, garlic (30%–60%) (Siddhu et al., 2018; Tripathy et al., 2013), rice (10%–100%), wheat (10%–60%) and potato (20%–30%) (Gharde & Singh, 2018). Herbicides remain the primary method of weed control, and agri-drones offer a practical option for both pre- and post-emergence spraying under diverse

field conditions. Chen et al. (2019) reported that UAV-applied pre-emergence herbicides caused no crop injury and provided 98%–100% weed control in humid, smooth soils, whereas post-emergence sprays resulted in 10%–20% crop injury and lower control efficiency (10%–70%). In comparison, knapsack sprayers performed better for post-emergence applications. Several studies have optimized UAV spraying parameters, including droplet size, spray volume, nozzle type and flight speed (Hunter et al., 2020; Shan et al., 2021). Hiremath et al. (2024) also found that, among knapsack, boom and UAV sprayers in soybean, the knapsack sprayer was most effective for weed management. Nutrient/bio-stimulants UAVs are increasingly used for foliar nutrient application, enabling rapid nutrient absorption and improving efficiency over soil application. UAV spraying with a 2% TNAU pulse wonder at 50 L/ha in green grams enhanced crop quality and yield compared to manual application (Dayana et al., 2022). Similarly, Kaniska et al. (2022) reported higher yields when NPK, micronutrients and humic acid were applied using a fuel-operated UAV at 30 L/acre. UAVs have also shown promise in grain biofortification; two UAV sprays of chelated Zn in rice produced Zn levels comparable to three manual $ZnNO_3$ sprays (Xu et al., 2021). As a low-volume method with high nutrient recovery and low residue risk, UAV foliar spraying is considered an efficient, eco-friendly option for nutrient delivery and biofortification.

3.6.2. Crop health monitoring of crops using UAVs UAVs are increasingly used for remote sensing and aerial crop monitoring, providing farmers with highresolution infrared and visual imagery to detect diseases, pests, weed emergence and other stresses (Table 3). Compared to satellite imagery, UAVs capture clearer, more detailed images because of their low-altitude and slow-flight operation. A wide range of sensors, including RGB, multispectral, hyperspectral, thermal and depth cameras are used depending on the monitoring objective (Neupane & Baysal-Gurel, 2021). Hyperspectral imaging can be used to differentiate the spectral signatures of various weed species (Huang et al., 2018). UAV-based sensing plays a key role in precision agriculture, enabling early detection of pests, diseases, weeds and abiotic stresses, allowing timely intervention. However, accurate image interpretation and automated analysis of large datasets remain major challenges. Several UAV-based systems have been

Table 3. Crop health monitoring using UAV. Crop Platform Disease and pest monitoring Olive and DJI Phantom 3 Advanced UAV with 3-axis 1080p full HD date palm video camera

Olive Quick Decline Syndrome caused by Xylella fastidiosa

Potato

Presence of the ‘red palm weevil Detection of potato beetle damage

Grape Radish Soybean Grape Cotton Tea Rice

‘Spreading Wings’ S800 hexacopter (DJI) With sensor of sixchannel Mini Multi Camera Array Long range DT-18 coupled with DT-5Bands imaging instrument having MicaSense RedEdgeTM sensor (Phantom 4, DJI co., Ltd.), equipped with an RGB camera (12 mega pixels) DJI Phantom 3 multi-rotor Mikrokopter OktoXL (HiSystems GmbH) equipped with a nadir-facing Tetracam ADC-lite camera Eight-rotor oktokopter (HiSystems GmbH) and multispectral TetraCam ADC camera DJI Matrice 600 pro with MicaSense RedEdge-M sensor

DJI inspire 2 Quad rotor UAV with a Sentera Multispectral Double 4 K sensor Plant stress monitoring Wheat DJI S1000 with Sony NEX-7 RGB camera Grapes ARF OktoXL 6S12 (HiSystems GmbH) with thermal infrared camera and multispectral digital camera Maize hexa-copter UAV with FLIR Vue Pro R 640 thermal camera Maize six-rotor unmanned aircraft DJI S900 with RGB, Thermal and multispectral camera

Purpose

Reference Psirofonia et al. (2017)

Hunt & Rondon (2017)

Detection of Flavescence dorée Grapevine Disease Fusarium wilt of radish

Albetis et al. (2017)

Soybean Foliar Diseases Grapevine leaf stripe disease

Tetila et al. (2017) Di Gennaro et al. (2016) Xavier et al. (2019)

Ramularia Leaf Blight Cotton Disease

Ha et al. (2017)

Monitoring Thosea sinensis Walker in Tea Plantations Monitoring narrow brown leaf spot severity

Yuan et al. (2023)

Drought Assessment Water Stress Assessment

Su et al. (2020) Zúñiga Espinoza et al. (2017) Zhang et al. (2019) Zhang et al. (2023)

Canopy Temperature Soil moisture content

Gu et al. (2023)

developed for specific applications. For example, AggieAir integrates RGB, NIR, and thermal sensors to estimate crop nitrogen, chlorophyll and soil moisture levels (Hassan-Esfahani et al., 2015). Thermal sensors have been used to assess grapevine water status via the Crop Water Stress Index (Santesteban et al., 2017). Multispectral UAV imaging combined with CNN-based machine learning has enabled effective monitoring of yellow rust in wheat (Su et al., 2020). UAV-mounted cameras have also been used to detect red palm weevil infestation in date palms (Psirofonia et al., 2017). In addition to crop health monitoring, UAVs support weed mapping (Huang et al., 2018; Lottes et al., 2017) and yield prediction (Mathivanan & Jayagopal, 2022). UAV-based multispectral imaging has also shown strong potential for assessing crop productivity. For example, a recent study demonstrated that vegetation indices derived from UAV multispectral imagery, combined with machine learning algorithms such as random forest and support vector machines, can accurately predict onion bulb yield across different planting dates and growth stages (Wayal et al., 2026). Recent advances in machine learning and deep learning have further enhanced the capability of UAVbased remote sensing by enabling efficient analysis and fusion of large and complex datasets. Emerging approaches such as foundation models and interpretable deep learning networks are increasingly being applied to hyperspectral and multimodal agricultural data. For instance, SpectralGPT, a spectral remote sensing foundation model, enables generalized feature learning across diverse spectral datasets, improving the robustness of crop monitoring applications (Hong et al., 2024). Similarly, LRR-Net (low-rank representation network) has been developed for interpretable hyperspectral anomaly detection, facilitating the identification of subtle crop stress signals (Li et al., 2024), while RustQNet, a multimodal deep learning framework, integrates spectral and visual information for the quantitative assessment of wheat stripe rust severity (Deng et al., 2024). These advances highlight the growing integration of artificial intelligence with UAV-based sensing systems, enabling more accurate, automated, and scalable crop health monitoring in precision agriculture. Key studies are summarized in Table 3. The availability of benchmark datasets plays a critical role in the development and evaluation of object detection models for UAV-based crop protection. Several publicly available datasets have been developed to support research on pest detection, disease identification and weed mapping using aerial imagery. These datasets typically include annotated RGB or multispectral UAV images and are widely used to train and benchmark deep learning models for agricultural applications. A summary of representative UAV-based datasets used for crop monitoring and protection is presented in Table 4.

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Table 4. Representative datasets used for UAV-based object detection in crop protection. Dataset PlantVillage DeepWeeds WeedMap Agriculture-Vision PestNet Deep Object Detection of Crop Weeds

Application Plant disease detection Weed detection Weed mapping Crop stress detection Insect pest detection Weed detection

Data type RGB images

Key features Large annotated dataset of crop diseases

RGB images UAV RGB imagery Aerial imagery RGB images

Dataset for weed classification using deep learning Pixel-level weed annotation in agricultural fields

Reference Singh & Gahlawat (2025) Olsen et al. (2019) Sa et al. (2018)

Large-scale aerial dataset for agricultural field analysis

Chiu et al. (2020)

Large insect pest dataset for crop protection research

Liu et al. (2019)

RGB images

more than 3000 RGB images of chicory plantations, collected using a UAV system at various stages of crop and weed growth

Gallo et al. (2023)

Figure 7. Factors to be considered while drone spraying.

3.6.3. Factors affecting the efficiency of agrochemical spray using UAV The bibliometric analysis of the retrieved documents highlights that factors such as flight height, flight speed, nozzle type, spray volume and spray mixture significantly influence the efficiency and precision of agrochemical spray using UAVs (Figure 7). These parameters are critical because they directly affect the resulting droplet size, density, drift and coverage. Consequently, optimizing or standardizing these variables for different crops and conditions is essential to achieve high efficiency and precision. The subsequent sections synthesize the literature focusing on these parameters, providing necessary guidelines for researchers, farmers and service providers to develop standard operating procedures (SOPs) for various UAV models and crops. Flight height and velocity Operational height and speed are critical factors influencing droplet deposition and uniformity in UAVbased agrochemical applications. In rice, optimal deposition was achieved at a height of 1.5 m and a speed of 5 m/s speed using a HyB-15L UAV (Qin et al., 2016). For cotton, effective defoliation occurred at 1.5 m with flight speeds of 3.12, 2.51 and 3.76 m/s for four-, six- and eight-rotor drones, respectively (Liao et al., 2019), while Lou et al. (2018) reported 2 m as the ideal height using a Jifei P20 UAV. A hexacopter study also reported that a depth of 1.5 m to provide the best spray uniformity (Hussain et al., 2019). For weed control with a single-rotor drone, maximum deposition was obtained at a height of 2 m and a speed of 2 m/s (Ahmad et al., 2020). Infrared thermal imaging studies have shown that increasing the flight speed reduces the droplet density, coverage and size (Lv et al., 2019). In sugarcane, a height of 3 m and a speed of 4 m/s ensure better deposition across canopy layers (Zhang et al., 2020). Similar evaluations have been conducted in peach orchards (Li et al., 2022; Meng et al., 2020), coffee plantations (Souza et al., 2022), and vineyards

(Biglia et al., 2022) to develop crop-specific SOPs. Thus, users must standardize flight height and speed based on crop characteristics, wind conditions and UAV type. Spray volume and nozzle Nozzle type, spray volume and liquid pressure are crucial determinants of droplet deposition and overall pesticide application efficiency in UAV spraying. Studies have shown that lower spray volumes with larger droplets enhance deposition (Fritz et al., 2006). Various nozzle types and sizes have been evaluated for their effects on droplet penetration, uniformity, drift and coverage (Derksen et al., 2008; Ferguson et al., 2016; Kirk, 2007; Zhu et al., 2006). Proper nozzle selection can significantly improve canopy penetration while reducing drift (Wolf & Daggupati, 2009). Owing to the limited number of drone-specific nozzles, flat-fan nozzles are widely used (He et al., 2018). Centrifugal nozzles (200–800 mL/min) are effective for aphid management in cotton (Lou et al., 2018). The spray volume strongly influences droplet deposition; in wheat, UAV deposition is comparable to that of knapsack sprayers when using > 16.8 L/ha and coarse nozzles (Wang et al., 2019). In vineyards, higher flight speeds improved deposition with conventional nozzles (Biglia et al., 2022). In rice, hydraulic nozzles showed higher droplet density, which is further enhanced by the use of adjuvants (Chen et al., 2020). Twin flat nozzles also produced greater deposition than single flat nozzles (Chojnacki & Pachuta, 2021). The cone and flat-fan nozzles showed maximum discharges of 646 and 827 mL/min, respectively (Kailashkumar et al., 2023). Spray drift remains a major concern in UAV applications. Wind-tunnel tests revealed that centrifugal nozzles pose higher drift risk than hydraulic nozzles, while adjuvants help reduce drift risk (Wang et al., 2020). Therefore, developing accurate drift prediction models is essential for safe UAV spraying. Pesticide formulation and adjuvants Although UAV use in agriculture is expanding rapidly, challenges such as droplet drift, pesticide bounceoff, and environmental risks persist. Recent studies highlight spray adjuvants as an effective strategy to

improve deposition and reduce drift. Wang et al. (2018) reported substantial drift reduction with various adjuvants, such as Silwet DRS-60 (65%), ASFA + B (62%), T1602 (59%), Break-thru Vibrant (46%), QF-LY (42%) and Tmax (19%), compared to water. Adjuvants have also improved spray performance at reduced pesticide doses, such as a 20% dose reduction for aphid control in wheat (Meng et al., 2018). Vegetable oil enhanced droplet coverage (Xiao et al., 2019), while a novel oil-in-water microemulsion of thiamethoxam and acetamiprid improved wettability and deposition (Song et al., 2020). Methylated vegetable oil increased the efficacy of prothioconazole against Fusarium head blight (Yan et al., 2021). In citrus canopies, tank-mix adjuvants increased droplet coverage and reduced leaf bounce using DJI T20 and T30 drones (Meng et al., 2022). Liu et al. (2023) demonstrated that both the nozzle type and the adjuvant strongly influence drift: SDS reduced drift by 69.2% (XR nozzle) and 66.3% (TXVK), while silicone adjuvant achieved a 78% reduction with the AIXR nozzle. However, some studies, such as Wang et al. (2022), reported no significant improvement in droplet deposition, though pest and disease control was still enhanced. Overall, adjuvants play a key role in improving UAV spray effectiveness and minimizing drift. Droplet size, density, coverage and penetration Droplet size and deposition are critical parameters in UAV-based agrochemical spraying. Key metrics include droplet density (number of droplets per unit area), deposition coverage (percentage of area covered by droplets) and arithmetic mean droplet size (Cunha et al., 2012; Subramanian et al., 2021). Deposition coverage is particularly important for evaluating spray efficiency. Studies have shown that UAV flight parameters strongly influence deposition. In rice, higher flight speed and height reduce droplet deposition, and wind direction and speed were identified as important considerations (Chen et al., 2016). Compared with UAVs, knapsack sprayers produce nearly double the droplet coverage, largely because of their higher spray volumes (250–300 L/ha vs. 15–20 L/ha for UAVs) (Xiao et al., 2020). Increased plant height and leaf area indices also reduced coverage in the lower canopy layers. Droplet size significantly affects deposition, penetration and drift. Larger droplets resulted in higher deposition, better canopy penetration, and lower drift, while very small droplets (<160 μm VMD) increased the drift risk. A 10 m buffer zone was recommended to minimize off-target movement (Chen et al., 2020). Droplet density increases with spray volume and is typically higher in the upper canopy than in the lower canopy (Xiao et al., 2020). Knapsack

sprayers also generate twice the droplet density of UAVs, again reflecting differences in spray volume. Uniform droplet distribution across upper, middle, and lower canopy layers remains a major challenge in UAV spraying, making it less consistent than conventional knapsack sprayers for uniform disease control. Economic viability Several studies have examined the economic rationale for adopting UAV technology in agriculture. Ramteke et al. (2025) reported significant savings in labour and pesticide use with UAV spraying. In China, UAV adoption increased revenue by $434–488 per hectare and reduced labour time by 14.4–15.8 h per hectare (Quan et al., 2023). Despite these benefits, high initial investment, high technical training requirements, and maintenance challenges remain key barriers (Ivezi et al., 2023). Although many researchers acknowledge the substantial upfront cost, they argue that long-term gains – particularly reduced labour and pesticide expenses often outweigh these initial expenditures (Huang et al., 2018), with some studies even indicating quick returns on investment (Safaeinezhad et al., 2025). Comparisons between UAV-based and traditional spraying methods commonly show that UAVs become more cost-effective over time because of their lower chemical use and labour requirements (Umeda et al., 2022). However, concerns persist regarding affordability for small-scale farmers, for whom the initial investment and maintenance costs may be prohibitive (Pathak et al., 2020). Differences in labour cost structures and farm size also contribute to inconsistent cost−efficiency assessments across studies. The lack of comprehensive economic data across diverse regions and production scales highlights the need for long-term, standardized cost evaluations to accurately compare UAV-based and conventional agricultural practices.

3.6.4. Advantages and disadvantages of UAVs in crop protection UAVs offer numerous advantages in crop protection, particularly in precision agriculture. The ability of these methods to provide real-time data enables farmers to accurately monitor crop health, allowing timely intervention. This technology is cost-effective, as it reduces the need for manual labour and minimizes the use of inputs such as water, fertilizers and pesticides, leading to significant savings. In addition, UAVs contribute to environmental benefits by ensuring that resources are used efficiently, thus reducing waste and environmental impacts. Owing to their high efficiency

and accuracy in covering large fields, UAVs are invaluable for modern farming practices (Figure 8). However, the use of UAVs for agriculture has several limitations. Operating agricultural UAVs requires special knowledge and skills, which poses a technical challenge for many farmers. These UAVs often have limited battery life, which restricts the duration and extent of their use. Many UAVs lack advanced features of collision avoidance and auto navigation that can limit their functionality in diverse farming scenarios. Regulatory issues such as the need for government registration and compliance with airspace regulations add another layer of complexity. UAVs are weather-sensitive and may not perform well under certain

Figure 8. Pros and cons of drone application in crop protection.

conditions. Additionally, their effectiveness may be limited for specific crops and problems, and there are concerns about privacy, as UAVs capture detailed images of private land.

- Discussion The bibliometric analysis reveals a growing interest in agricultural research, particularly in areas such as remote sensing and precision agriculture. The increase in publications around 2020 could be linked to advancements in technology and the need for sustainable agricultural practices. The increase in publications, indicates a growing interest and investment in research related to agriculture and crop protection. This trend may be driven by the need for sustainable agricultural practices and the integration of technology in farming (Anam et al., 2024). The dominance of Chinese institutions in research output underscores China's investment in agricultural sciences. The leading role of Chinese institutions, such as ‘China Agricultural University’ and ‘South China Agricultural University’, highlights China's significant investment in agricultural research. This is consistent with China's strategic focus on food security and agricultural modernization, including massive government funding supporting UAV innovation and agricultural mechanization (Wang et al., 2023). The variety of journals and international authors indicates a multidisciplinary approach to addressing agricultural challenges. The prominence of ‘Remote Sensing’ and ‘Agronomy’ as the most relevant sources suggests a strong focus on technological applications and agricultural sciences. Remote sensing technologies are increasingly used for precision agriculture, which aligns with the global trend towards data-driven farming practices (López-Granados et al., 2020). The analysis reveals that China and the USA are the leading contributors to research in this field, both in terms of publication volume and citation impact. Similar results were reported by Singh et al. (2022), where USA and China were leading contributors to the research output of the use of UAV in precision agriculture. The high level of international collaboration, as indicated by the MCP and SCP, suggests a global effort to address agricultural challenges. The USA’s high MCP and citation impact suggest strong international partnerships, particularly in areas such as precision agriculture and robotics. The most cited documents and the word cloud emphasize the importance of advanced technologies such as remote sensing, deep learning, and computer vision in modern agriculture. These insights reflect the field's focus on leveraging technology to improve agricultural efficiency and sustainability. The focus on ‘agricultural robots’ and ‘herbicide application’ signals a shift toward automation to address labour shortages and environmental concerns. Research on AI-driven decision systems (Gupta et al., 2020) is likely to grow, as evidenced by the rapid citation of recent papers. The active participation of various countries and the high citation counts indicate a vibrant and impactful research community. The co-occurrence analysis reveals a strong emphasis on integrating advanced technologies such as AI, machine learning, and remote sensing into agricultural practices. The prominence of precision agriculture and site-specific management techniques indicates a shift towards more efficient and sustainable farming methods. The prominence of ‘artificial intelligence’, ‘machine learning’ and ‘deep learning’ reflects a paradigm shift toward data-driven decision-making in agriculture. AI applications, such as weed detection and crop health monitoring, are increasingly used to optimize resource use and reduce environmental impacts (Kamilaris & Prenafeta-Boldú, 2018). For example, AI-powered UAVs enable real-time weed mapping, reducing herbicide overuse (Lottes et al., 2017). The focus on weed management and herbicide application highlights the ongoing challenges in crop protection and the need for innovative solutions. Terms such as ‘weed detection’, ‘weed mapping’ and ‘site-specific weed management’ emphasize efforts to minimize herbicide use through targeted interventions. This aligns with global trends toward sustainable agriculture, where precision technologies reduce chemical runoff and environmental harm (Getahun et al., 2024). The interconnectedness of these themes suggests a

multidisciplinary approach, where technology, environmental science, and agronomy converge to address complex agricultural issues. The use of UAVs for tasks such as aerial spraying and weed mapping demonstrates the practical application of these technologies in the field. UAVs are widely adopted for tasks such as aerial imaging, pesticide application, and normalized difference vegetation index (NDVI)-based crop monitoring, enhancing efficiency in large-scale farming (Zhang & Kovacs, 2012). Their integration with computer vision (e.g. weed detection) supports sitespecific management, a cornerstone of precision agriculture (Torres-Sánchez et al., 2015). Overall, the analysis underscores the transformative impact of technology on agriculture, driving advancements in

precision farming, sustainable practices and efficient resource management. The research community is actively exploring ways to leverage these technologies for crop protection to enhance productivity while minimizing environmental impacts. Despite the rapid advancement of UAV-based crop protection technologies, several challenges still limit their large-scale practical deployment. One of the major constraints is the limited availability of high-quality, annotated datasets for training robust machine learning and deep learning models, which often affects model generalization across crops, environments and growing seasons (Huang et al., 2025; Joshi et al., 2023). In addition, real-time processing of large volumes of UAV imagery and the integration of data from multiple sensors (e.g. RGB, multispectral, hyperspectral and thermal) remain significant technical challenges (Zhang & Zhu, 2023). Future research should therefore focus on developing standardized datasets, improving cross-sensor data fusion techniques, and designing lightweight, real-time analytics frameworks that can support scalable and operational UAV-based crop protection systems.

- Conclusion In conclusion, this study has examined the escalating use of UAVs for crop protection. Bibliometric and cooccurrence analyses reveal that this field is experiencing rapid growth with substantial contributions tracing from China and the USA, which dominate both publication output and citation metrics. This research heavily focuses on integrating advanced technologies, such as AI and remote sensing, into precision agriculture, as evidenced by co-occurrence analysis. Despite encouraging advancements, few studies have critically addressed the practical challenges encountered while implementing these technologies across diverse agricultural landscapes. Overall, this investigation delineates a dynamic and interdisciplinary research landscape that fosters driving innovations in agricultural technology and sustainable farming practices, which is particularly applicable in developing agrarian countries. To optimize the application of agrochemicals via UAVs, careful consideration must be given to spray parameters such as spray velocity, height, nozzle type, spray volume, and spray mixture tailored to specific crops, purposes and environmental conditions. The advantages of UAV spraying, such as enhanced access to challenging terrains, reduced human exposure to pesticides, decreased chemical usage, and labour and time savings, highlight its potential benefits. However, it is essential to carefully assess and mitigate agrochemical drift by selecting appropriate nozzles and adjuvants. Additionally, rigorous assessment of pesticide efficacy is necessary to determine the optimal dosage and application frequency. Future research directions should prioritize the development of sustainable custom hiring models for UAV usage and establish frameworks for effective data sharing to support the maintenance of machine learning and deep learning models. Notably absent from the current discourse are specific bibliometric analyses pertinent to these areas, which could serve as critical dimensions for future studies. Key recommendations for further exploration include investigating targeted efficacy trials focused on optimizing pesticide dosage and frequency for UAV applications that conduct life cycle assessments on UAV-based agricultural applications to inform sustainable custom hiring strategies, developing comprehensive frameworks for UAV data sharing aimed at preserving and enhancing machine learning and deep learning models for applications such as yield prediction and stress characterization. There are limited data on the long-term environmental impacts of UAV-sprayed chemicals, particularly concerning their effects on beneficial insects and soil health. Addressing these gaps will not only enrich the understanding of UAV technologies in agriculture but also facilitate the successful implementation of these innovations in varied agricultural contexts.

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Bibwe: Data curation, Methodology, Resources, Supervision, Writing – review & editing; Bhaskar Gaikwad: Formal analysis, Methodology, Resources, Validation, Writing – review & editing; Rohini Bhat: Data curation, Investigation, Writing – original draft, Writing – review & editing; Suresh J. Gawande: Conceptualization, Resources, Writing – review & editing; Vijay Mahajan: Funding acquisition, Resources, Writing – review & editing.

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Application of drone in agriculture: A review Gopal Dutta and Purba Goswami DOI: https://doi.org/10.22271/chemi.2020.v8.i5d.10529 Abstract The population is increasing tremendously and with this increase the demand of food. The traditional methods which were used by the farmers were not sufficient enough to fulfil these requirements. Thus, new automated methods (Drone technology) were introduced. These new methods satisfied the food requirements and also provided employment opportunities to billions of people. Drones technologies saves the excess use of water, pesticides, and herbicides, maintains the fertility of the soil, also helps in the efficient use of man power and elevate the productivity and improve the quality. The objective of this paper is to review the usage of Drones in agriculture applications. Based on the literature, we found that a lot of agriculture applications can be done by using Drone. In the methodology, we used a comprehensive review from other researches in this world. This paper summarizes the current state of drone technology for agricultural uses, including crop health monitoring and farm operations like weed management, Evapotranspiration estimation, spraying etc. The research article concludes by recommending that more farmers invest in drone technology to better their agricultural outputs. Keywords: Drone, crop health monitoring, evapotranspiration, spraying

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Introduction As much as India depends upon the agriculture, still it is far short from adapting latest technologies in it to get good farm. Developed countries have already started use of UAV’s in their precision agriculture [1, 2], photogrammetry and remote sensing [3, 4]. It is very fast and it could reduce the work load of a farmer. In general, UAVs are equipped with the cameras and sensors for crop monitoring and sprayers for pesticide spraying. In the past, variety of UAV models running on military and civilian applications [5]. A technical analysis of UAVs in precision agriculture is to analyze their applicability in agriculture operations like crop monitoring [6], crop height Estimations [7], pesticide Spraying [8], soil and field analysis [9]. However, their hardware implementations [10] are purely depended on critical aspects like weight, range of flight, payload, configuration and their costs. Drones have long been thought of as expensive toys. One area that has

seen little attention from drones, perhaps to its detriment, is the agricultural sector. Drones can fly autonomously with dedicated software which allows making a flight plan and deploying the system with GPS and feed in various parameters such as speed, altitude, ROI (Region of Interest), geo-fence and fail-safe modes. Drones are preferred over full size aircrafts due to major factors like combination of high spatial resolution and fast turnaround capabilities together with low operation cost and easy to trigger. These features are required in precision agriculture where large areas are monitored and analyses are carried out in minimum time. Using of aerial vehicle is possible due to miniaturization of compact cameras and other sensors like infrared and sonar. The Japanese were the first to successfully apply UAS technology to agricultural chemical spraying applications in 1980's [11], and crop dusting in the 1990's. As of 2001 1,220 units of Yamaha unmanned helicopters had been sold and were in use in Japan [12]. Over 2,000 Yamaha RMAX unmanned hellos spray about 2.5 million acres a year, covering about 40% of the country's rice paddies in Japan [12]. U.S. is behind Japan in UAV agricultural applications, and advocates have to navigate through a minefield of privacy and legal issues in order to legally implement them into society. Although the use of UAVs in agriculture has been steadily increasing, such growth is hindered by many technical challenges that still need to be overcome. Among those applications, stress detections and quantification is arguably the one that has received the greatest amount of attention, most likely due to the potential positive ~ 181 ~

impact that early stress detection can have on the agricultural activity. As a consequence, a large amount of data has been generated and a wide variety of strategies have been proposed, making it difficult to keep track of the current state of the art on the subject and the main challenges yet to be overcome. In this context, the objective of this article is to provide a comprehensive overview of the application of Drone (UAVs) in agriculture to monitor and assess plant stresses such as drought, diseases, nutrition deficiencies, pests, and weeds etc. Crop monitoring for insects, nutrients, disease, water-stress, and overall plant health is an important aspect of precision agriculture operations. This has been carried out by examination from the air or on the ground traditionally, but

these methods are limited by cost of operation and availability. Imagery created using light aircraft usually has higher resolution, is cheaper and more up to date, but it is still relatively expensive per acre. Small UAV or UAS can be used to acquire temporal/spatial data with a resolution of centimetres, and can fly consistently with repeatability of route and altitude to continuously cover the crop's fields. The acquisition of the images by UAVs is manageable and not as influenced by cloud cover. As indicated, UAS has been used in many areas in agriculture, although they still have many limitations and challenges to overcome. This paper summarizes major UAS applications and technologies for agriculture, and discusses the challenges of using UAS in an agricultural context.

Crop health monitoring Drones can be used for monitoring the conditions of crops throughout the crop season so that the need-based and timely action can be taken. By using different kinds of sensors pertaining to visible, NIR and thermal infrared rays, different multispectral indices can be computed based on the reflection pattern at different wavelengths. These indices can be used to assess the conditions of crops like water stress, nutrient stress, insect-pest attack, diseases, etc. The sensors present over the drones can see the incidence of diseases or deficiency even before the appearance of visible symptoms. Thus, they serve as a tool for early detection of the diseases. In this way, drones can be used for early warning system so that timely action can be taken by applying the remedial measures based on the degree of the stress. UAVs (Drone) are capable of observing the crop with different indices [13]. The UAVs are able to cover up hectares of fields in single flight. For this observation thermal and multi spectral Cameras [14] to record reflectance of vegetation canopy, which is mounted to downside of the quad copter. The camera takes one capture per second and stores it into memory and sends to the ground station through telemetry. The data coming from the multispectral camera through telemetry was analysed by the Geographic indicator Normalized Difference Vegetation Index (NDVI) [15] represented in equation.

Normalization difference vegetation index is a simple metric which indicates the health of green vegetation. The basic theory is chlorophyll strongly reflects near infrared light (NIR, around 750nm) while red and blue are absorbed. Chlorophyll reflects strongly which is why plants appear green to us but reflection in NIR in even greater, this plays a very important role and helps in rendering precise data for analysis. The calculations gives the values -1 to +1; near to 0 (ZERO) indicates no vegetation on the crop and near to +1 (0.8 to 0.9) means

highest density of green leaves on the crop [12] . Based upon these result farmers easily identify crop health condition also monitoring crops. Based upon these results, farmers easily identify the field where can spray the pesticides. Drones can be used for monitoring the conditions of crops throughout the crop season so that the need-based and timely action can be taken. The quick and appropriate action can prevent yield loss. This technology will eliminate the need to visually inspecting the crops by the farmers. They can monitor the horticultural crops or other crops present in remote areas like mountainous regions. They can also monitor the tall crops and trees efficiently, which are otherwise challenging to scout physically by farmers.

NDVI = (RNIR – RRED)/ (RNIR + RRED) RNIR = Reflectance of the near infrared band. RRED = Reflectance of the red band.

Water stress monitoring: The characterization of water stress on crops is a complex task because the effects of drought affect (and can be affected by) several factors [16]. Variables derived from thermal images often rely on very slight temperature variations to detect stresses and other phenomena. As a result, thresholds and regression equations derived under certain conditions usually do not hold under even slightly different circumstances. For

example, different genotypes of a given crop may present significantly different canopy temperatures under the same conditions due to inherent differences in stomatal conductance and transpiration rates [17, 18, 19]. Researchers used various types of sensors and model to identify water stresses: Using multispectral or hyper spectral images and the vegetation indices (NDVI, GNDVI, etc.) used in References [16, 20] are the result of spectral transformations aiming at highlighting certain vegetation properties. Using multispectral or hyper spectral images and the photochemical reflectance index (PRI) used in References [17, 20, 21] is a reflectance measurement sensitive to changes in carotenoid pigments present in leaves. Using thermal infrared imagery and the difference between the canopy and air temperatures (T c - Ta) used in Reference [18]; some studies use the canopy temperature directly [16, 22]. Using thermal infrared imagery and the crop water stress index (CWSI), used in References [18, 19, 21] is based on the difference between canopy temperature and air temperature (Tc - Ta), normalized by the vapour pressure deficit (VPD) [21]. A related variable, called Non Water Stress Baseline (NWSB), was also used in some investigations [23]. The rationale behind this is that water stress induces a decrease in stomatal conductance and less heat dissipation in plants, causing a detectable increase in the canopy temperature [16, 24]. Red-Green-Blue (RGB) images have been employed sparingly, usually associated with multispectral or thermal images for the calculation of hybrid variables such as the Water Deficit Index (WDI) [24]. Chlorophyll fluorescence, calculated using narrow-band multispectral images, has also been sporadically applied to the problem of water stress detection and monitoring [20, 25]. Nutrient status and deficiency monitoring: Plants need the appropriate levels of nutrients in order to thrive and produce a strong yield. The appropriate levels of nitrogen will ensure strong growth of vegetation and foliage, appropriate levels of phosphorous are required for strong root and stem growth and appropriate levels of potassium are necessary for improving of the resistance to disease and also to ensure a better quality of crop. If soil lacks any of these nutrients, the plant will become stressed and will struggle to thrive. NDVI Index mosaics offer the possibility to identify exactly which areas of the crops are stressed or struggling and to target directly these areas. The NIR/multispectral imagery provided by the UAVs can identify these management zones long before the problem become visible to the naked eye. This means that these management zones can be targeted before crop development and yield is affected. Currently, the most common way to determine the nutritional status is visually, by means of plant colour guides that do not allow quantitatively rigorous assessments [26]. More accurate evaluations require laboratorial leaf analyses, which are time consuming and require the application of specific methods for a correct interpretation of the data [27]. There are some indirect alternatives available for some nutrients, such as the chlorophyll meter (Soil-plant analyses development (SPAD) for nitrogen predictions [28], but this is a time consuming process [29] and the estimates are not always accurate [30]. Thus, considerable effort has been dedicated to the development of new methods for the detection and estimation of nutritional problems in plants [31]. Nitrogen is, by far, the most studied nutrient due to its connection to biomass and yield. Potassium and sodium [32]

have also received some attention. Multispectral images have been the predominant choice for the extraction of meaningful features and indices [33, 34], but RGB [35] and hyper spectral images [33] are also frequently

adopted. Data fusion combining two or even three types of sensors (multispectral, RGB, and thermal) has also been investigated [35]. The vast majority of the studies found in the literature extracts vegetation indices (VI) from the images and relates them with nutrient content using a regression model (usually linear). Although less common, other types of variables have also been used to feed the regression models, such as the average reflectance spectra [32], selected spectral bands [34], colour features [36], and principal components [37]. All of these are calculated from hyper spectral images, except the colour features, which are calculated from RGB images. Diseases monitoring Crop diseases can be devastating and classified as fungal, bacterial or viral. Drones equipped with Infrared cameras can see inside plants [38], giving a clear image of the condition thereof. If a farmer can detect an infection before it spreads, preventative measures can be taken - like removing the plant before the infection spreads to neighbour plants. Image-based tools can, thus, play an important role in detecting and recognizing plant diseases when human assessment is unsuitable, unreliable, or unavailable [39], especially with the extended coverage provided by UAVs. RGB [39, 40] and multispectral images [41, 42] have been preferred methods for acquiring information about the studied areas, but hyper spectral [43, 44] and thermal images [43, 44] have also been tested. The latter is employed mostly to detect water stress signs potentially caused by the targeted disease. Weed Control Weeds are not desirable plants, which grow in agricultural crops and can cause several problems. They are competing for available resources such as water or even space, causing losses to crop yields and in their growth. Yield losses due to weed in India: Rice (10-100%), Wheat (10-60%), Maize (3040%), Sugarcane (25-50%), Vegetables (30-40%), Jute (3070%), Potato (20-30%) etc. [45]. The use of herbicides is the dominant choice for weed control. In conventional farming, Farmers uprooted weeds after post emergence and the most common practice of weed management is to spray the same amounts of herbicides over the entire field, even within the weed-free areas. However, the overuse of herbicides can result in the evolution of herbicide-resistant weeds and it can affect the growth and yield of the crops. Using hyperspectral images to discriminate between the spectral signatures of some weeds with different resistances to glyphosate [46]. Using RGB sensors to classify various weed species [47]. Researchers used drone with hyper spectral sensors to monitor weed as a function of the plant canopy chlorophyll content and leaf density [48]. In addition, it poses a heavy pollution threat to the environment. To overcome the above problems site specific weed management is used to achieve this goal, it is necessary to generate an accurate weed cover map for precise spraying of herbicide. Drone can gather images and derive data from the whole field that can be used to generate a precise weed cover map depicting the spots where the chemicals are needed. Agro-drone application for weedicide spray useful for preemergence & post emergence weed control. Spraying is possible in any field condition (muddy, weeds, insects etc.) also in sunny and drizzling condition. Weedicide application

through drone is efficient and optimizes uses of weedicide. It is simple to use and easy to carry and maintain. Operate remotely that is very safe for health. Drone for Evapotranspiration (ET) estimation Evapotranspiration (ET) is an important process by which water is transferred from the land to the atmosphere by evaporation from the soil and by transpiration from living plants. Estimates of potential ET are used by professionals in the fields of hydrology, agriculture, and water management. Estimating evapotranspiration has been one of the most important researches in agriculture recently because of water scarcity, growing population, and climate change. Many kinds of unmanned aerial vehicles are used on different research purposes for ET estimation. Typically, there are three different UAV platforms, aircraft, fixed-wings, and quad copter. Aircraft is usually expensive, but it can fly longer and carry heavy sensors. Compared with aircraft, fixed-wings and quadcopter are less expensive. Fixed-wings can usually fly about 2 hours, which is suitable for a large scale of field. Quadcopter can fly about 30 minutes, which is used for short flight mission in a small scale of field. Being used as a remote sensing platform, UAVs also arouse new research problems, such as drone image processing, and flight path planning. A fixed-wing UAV to collect thermal data to estimate ET with two source energy balance models [49]. Evapotranspiration in a peach orchard estimated by using very-high-resolution imagery from an UAV platform (S1000, DJI, Shenzhen, China) [50]. A TIR camera (A65, FLIR Systems Inc.) and a multispectral camera RedEdge (MicaSense, Seattle, WA, USA) are also mounted on the drone. Multispectral and thermal images were collected by using an airborne digital system for estimation of evapotranspiration, developed by Utah State University [50]. The spectral bands for these cameras are, Red (0.645 μm - 0.655 μm), Green (0.545 μm – 0.555 μm), Blue (0.465 μm – 0.475 μm) and Near-infrared (NIR) (0.780 μm – 0.820 μm). A Thermal CAM

SC640 (FLIR Systems Inc.) is also mounted on the aircraft to collect thermal infrared (TIR) images; the wavelength range is 7.5 μm – 13 μm. Compared with other satellites based remote sensing methods, UAV platform and light weight sensors can provide better quality, higher spatial and temporal resolution images [51]. Spraying Indian agriculture needed production and protection materials to achieve high productivity. Agriculture fertilizer and chemical frequently needed to kill insects and the growth of crops. Drones can be used to spray chemicals like fertilizers, pesticides, etc. based on the spatial variability of the crops and field. The amount of chemicals to be sprayed can be adjusted depending upon the crop conditions, or the degree of severity of the insect-pest attack. The integration of UAV with sprayer system results a potential to provide a platform to pest management and vector control. This is accurate site specific application for a large crop fields. For this purpose heavy lift UAVs [52, 53] are required for large area of spraying. Researcher proposed the Quad copter (QC) system which is low cost, and lightweight, also known as Unmanned Aerial Vehicle (UAV) [54]. These quadcopter is small size, and this system can be used for indoor crops as well as outdoor crops. Quadcopter is an autonomous flight for spraying pesticides and fertilizer using the android device. Between the quadcopter and android device communication is done by Bluetooth device in real time operation. This system is used to

reduce agriculture field related problems, and also increases the yield of agriculture. The efficiency of the spraying system which is mounted to the UAV increases through the PWM controller [55, 56] in the pesticide applications. A blimp integrated quad copter aerial automated pesticide sprayer (AAPS) was developed for pesticide spraying based on the GPS coordinates in lower altitude environment [57]. To, overcome this low cost user flexible pesticide spraying drone “Freyr” was developed which is controlled by an android app [58] . A laboratory and field evolutions are analyzed for discharge and pressure rate of the liquid, spray uniformity and liquid loss, droplet density and sizes of a developed hexa copter mounted sprayer [59]. To reduce the wastage of pesticides an electrostatic sprayer introduced and designed on electrostatic spray technology with a hexa rotor UAV [60]. The WHO (World Health Organization) estimates there are more than 1 million pesticide cases every year. In that more than one lakh deaths each year, especially in developing countries due to the pesticides sprayed by a human being. The pesticide affects the nervous system of human and leads to disorders in the body. A remote controlled UAV (Unmanned Aerial Vehicle) is used to spray the Pesticide as well as fertilizer to avoid the humans from pesticide poison [61]. Crop dusting: Drones able to carry tanks of fertilizers and pesticides to spray crops with far more precision than a tractor. This helps reduce costs and potential pesticide exposure to workers who would have needed to spray those crops manually [62]. Pesticide application by drone can be used in all situations, especially in the places where labours are hard to find, environmental pollution can be reduced when it sprayed from lower altitude also it has a great potential to enhance pest management for small as well as the large crop field to entail highly accurate site-specification application [63]. Some scientist studied the impact of UAV (UAV N-3) spraying parameters at different working height and varying concentration of spraying pesticide on the wheat canopy and the prevention of powdery mildew in Asian countries [64]. This ultimately increases the efficiency of the chemicals applied, thereby reducing their adverse impacts on the environment by decreasing the soil and water pollution. Thus, it can lead towards sustainable agriculture. Drones spray chemicals at a faster rate as compared to other methods. It can also result in the saving of the amount of chemicals applied, which can reduce input cost. A major economic input for any agricultural season is the application of fertilizers (e.g., nitrogen, phosphate, potash), and micronutrients (e.g., sulphur, magnesium, zinc). Fertilizer is applied by on-ground equipment (tractor powered sprayers or pressurized irrigation systems) [65] or by manned aircraft [66] . The latter is the most preferred by producers with multiple and large land units. They generally use a single application rate for all fields being sprayed because changing wind speed and direction conditions during fertilizer application and the elevation of the aircraft make more precise application impossible. Ground equipment application is used as a complement to aerial spraying to maintain stable crop nutrient status across the irrigation season. UAV estimation of crop nutrient status can directly benefit the application rate recommendations by producer or agronomist consultant by including the entirety of the field. Research efforts indicate that it is possible to perform the monitoring with scientific UAVs and specialized camera sensors such as optical and thermal cameras [67, 68] along with specialized optical filters such as Red Edge or hyper spectral cameras [69, 70, 71]. Accelerometer and Gyroscope Sensors were used for spraying fertilizer and pesticide; it has ability to reduce time and human efforts [72].

Table 1: References dealing with the application of drones in various cases ~ 184 ~

Application Water Stress Monitoring Nutrient Disorders Diseases Monitoring Weeding Evapotranspiration Spraying

Sensor/ model used Multispectral or Hyperspectral sensors and NDVI, GNDVI and PRI model Thermal infrared sensor and Canopy temperature, canopy temp.-Air temp. (Tc - Ta) RGB Sensor & WDI RGB, Multispectral and Hyperspectral sensors RGB sensor Multispectral images sensor Hyperspectral and thermal sensor Hyperspectral sensor RGB sensors Multispectral and thermal sensor GPS sensor Accelerometer and Gyroscope Sensors

Conclusion Drones have great potential to transform Indian agriculture. With the advancement of technology in the future, the production of drones is expected to become economical. The modern youth are not attracted towards farming due to hard work and drudgery involved in it. The implication of drones may fascinate and encourage the youth towards agriculture. Drones provide real time and high quality aerial imagery compared to satellite imagery over agricultural areas. Also, applications for localizing weeds and diseases, determining soil properties, detecting vegetation differences and the production of an accurate elevation models are currently possible with the help of drones. Drones will enable farmers to know more about their fields. Therefore, farmers will be assisted with producing more food while using fewer chemicals. Nearly all farmers who have made use of drones have achieved some form of benefit. They can make more efficient use of their land, exterminate pests before they destroy entire crops, adjust the soil quality to improve growth in problem areas, improve irrigation to plants suffering from heat stress and track fires before they get out of control. Therefore, drones may become part and parcel of agriculture in the future by helping farmers in managing their fields and resources in a better and sustainable way. Reference 1. Aditya S Natu, Kulkarni SC. Adoption and Utilization of Drones for Advanced Precision Farming: A Review. published in International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169. 2016; 4(5):563-565. 2. Zhang C, Kovacs JM. The application of small unmanned aerial systems for precision agriculture: a review. Precision agriculture, Springer. 2012; 13(6):693-712. 3. Everaerts J. The use of unmanned aerial vehicles (UAVs) for remote sensing and mapping. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2008; 37:1187-1192. 4. Colomina I, Molina P. “Unmanned aerial systems for photogrammetry and remote sensing: A review.”ISPRS Journal of Photogrammetry and Remote Sensing. 2014; 92:79-97. 5. Van Blyenburgh P. UAVs: an overview. Air & Space Europe. 1999; 1(5-6):43-47. 6. Bendig J, Bolten A, Bareth G. Introducing a low-cost mini-UAV for thermal-and multispectral-imaging. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2012; 39:345-349. 7. Anthony D, Elbaum S, Lorenz A, Detweiler C. On crop height estimation with UAVs. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2014), 2014, 4805-4812.

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Application of drone in agriculture: A review Gopal Dutta and Purba Goswami DOI: https://doi.org/10.22271/chemi.2020.v8.i5d.10529 Abstract The population is increasing tremendously and with this increase the demand of food. The traditional methods which were used by the farmers were not sufficient enough to fulfil these requirements. Thus, new automated methods (Drone technology) were introduced. These new methods satisfied the food requirements and also provided employment opportunities to billions of people. Drones technologies saves the excess use of water, pesticides, and herbicides, maintains the fertility of the soil, also helps in the efficient use of man power and elevate the productivity and improve the quality. The objective of this paper is to review the usage of Drones in agriculture applications. Based on the literature, we found that a lot of agriculture applications can be done by using Drone. In the methodology, we used a comprehensive review from other researches in this world. This paper summarizes the current state of drone technology for agricultural uses, including crop health monitoring and farm operations like weed management, Evapotranspiration estimation, spraying etc. The research article concludes by recommending that more farmers invest in drone technology to better their agricultural outputs. Keywords: Drone, crop health monitoring, evapotranspiration, spraying

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Introduction As much as India depends upon the agriculture, still it is far short from adapting latest technologies in it to get good farm. Developed countries have already started use of UAV’s in their precision agriculture [1, 2], photogrammetry and remote sensing [3, 4]. It is very fast and it could reduce the work load of a farmer. In general, UAVs are equipped with the cameras and sensors for crop monitoring and sprayers for pesticide spraying. In the past, variety of UAV models running on military and civilian applications [5]. A technical analysis of UAVs in precision agriculture is to analyze their applicability in agriculture operations like crop monitoring [6], crop height Estimations [7], pesticide Spraying [8], soil and field analysis [9]. However, their hardware implementations [10] are purely depended on critical aspects like weight, range of flight, payload, configuration and their costs. Drones have long been thought of as expensive toys. One area that has seen little attention from drones, perhaps to its detriment, is the agricultural sector. Drones can fly autonomously with dedicated software which allows making a flight plan and deploying the system with GPS and feed in various parameters such as speed, altitude, ROI (Region of Interest), geo-fence and fail-safe modes. Drones are preferred over full size aircrafts due to major factors like combination of high spatial resolution and fast turnaround capabilities together with low operation cost and easy to trigger. These features are required in precision agriculture where large areas are monitored and analyses are carried out in minimum

time. Using of aerial vehicle is possible due to miniaturization of compact cameras and other sensors like infrared and sonar. The Japanese were the first to successfully apply UAS technology to agricultural chemical spraying applications in 1980's [11], and crop dusting in the 1990's. As of 2001 1,220 units of Yamaha unmanned helicopters had been sold and were in use in Japan [12]. Over 2,000 Yamaha RMAX unmanned hellos spray about 2.5 million acres a year, covering about 40% of the country's rice paddies in Japan [12]. U.S. is behind Japan in UAV agricultural applications, and advocates have to navigate through a minefield of privacy and legal issues in order to legally implement them into society. Although the use of UAVs in agriculture has been steadily increasing, such growth is hindered by many technical challenges that still need to be overcome. Among those applications, stress detections and quantification is arguably the one that has received the greatest amount of attention, most likely due to the potential positive ~ 181 ~

impact that early stress detection can have on the agricultural activity. As a consequence, a large amount of data has been generated and a wide variety of strategies have been proposed, making it difficult to keep track of the current state of the art on the subject and the main challenges yet to be overcome. In this context, the objective of this article is to provide a comprehensive overview of the application of Drone (UAVs) in agriculture to monitor and assess plant stresses such as drought, diseases, nutrition deficiencies, pests, and weeds etc. Crop monitoring for insects, nutrients, disease, water-stress, and overall plant health is an important aspect of precision agriculture operations. This has been carried out by examination from the air or on the ground traditionally, but

these methods are limited by cost of operation and availability. Imagery created using light aircraft usually has higher resolution, is cheaper and more up to date, but it is still relatively expensive per acre. Small UAV or UAS can be used to acquire temporal/spatial data with a resolution of centimetres, and can fly consistently with repeatability of route and altitude to continuously cover the crop's fields. The acquisition of the images by UAVs is manageable and not as influenced by cloud cover. As indicated, UAS has been used in many areas in agriculture, although they still have many limitations and challenges to overcome. This paper summarizes major UAS applications and technologies for agriculture, and discusses the challenges of using UAS in an agricultural context.

Crop health monitoring Drones can be used for monitoring the conditions of crops throughout the crop season so that the need-based and timely action can be taken. By using different kinds of sensors pertaining to visible, NIR and thermal infrared rays, different multispectral indices can be computed based on the reflection pattern at different wavelengths. These indices can be used to assess the conditions of crops like water stress, nutrient stress, insect-pest attack, diseases, etc. The sensors present over the drones can see the incidence of diseases or deficiency even before the appearance of visible symptoms. Thus, they serve as a tool for early detection of the diseases. In this way, drones can be used for early warning system so that timely action can be taken by applying the remedial measures based on the degree of the stress. UAVs (Drone) are capable of observing the crop with different indices [13]. The UAVs are able to cover up hectares of fields in single flight. For this observation thermal and multi spectral Cameras [14] to record reflectance of vegetation canopy, which is mounted to downside of the quad copter. The camera takes one capture per second and stores it into memory and sends to the ground station through telemetry. The data coming from the multispectral camera through telemetry was analysed by the Geographic indicator Normalized Difference Vegetation Index (NDVI) [15] represented in equation.

Normalization difference vegetation index is a simple metric which indicates the health of green vegetation. The basic theory is chlorophyll strongly reflects near infrared light (NIR, around 750nm) while red and blue are absorbed. Chlorophyll reflects strongly which is why plants appear green to us but reflection in NIR in even greater, this plays a very important role and helps in rendering precise data for analysis. The calculations gives the values -1 to +1; near to 0 (ZERO) indicates no vegetation on the crop and near to +1 (0.8 to 0.9) means highest density of green leaves on the crop [12] . Based upon these result farmers easily identify crop health condition also monitoring crops. Based upon these results, farmers easily identify the field where can spray the pesticides. Drones can be used for monitoring the conditions of crops throughout the crop season so that the need-based and timely action can be taken. The quick and appropriate action can prevent yield loss. This technology will eliminate the need to visually inspecting the crops by the farmers. They can monitor the

horticultural crops or other crops present in remote areas like mountainous regions. They can also monitor the tall crops and trees efficiently, which are otherwise challenging to scout physically by farmers.

NDVI = (RNIR – RRED)/ (RNIR + RRED) RNIR = Reflectance of the near infrared band. RRED = Reflectance of the red band.

Water stress monitoring: The characterization of water stress on crops is a complex task because the effects of drought affect (and can be affected by) several factors [16]. Variables derived from thermal images often rely on very slight temperature variations to detect stresses and other phenomena. As a result, thresholds and regression equations derived under certain conditions usually do not hold under even slightly different circumstances. For

example, different genotypes of a given crop may present significantly different canopy temperatures under the same conditions due to inherent differences in stomatal conductance and transpiration rates [17, 18, 19]. Researchers used various types of sensors and model to identify water stresses: Using multispectral or hyper spectral images and the vegetation indices (NDVI, GNDVI, etc.) used in References [16, 20] are the result of spectral transformations aiming at highlighting certain vegetation properties. Using multispectral or hyper spectral images and the photochemical reflectance index (PRI) used in References [17, 20, 21] is a reflectance measurement sensitive to changes in carotenoid pigments present in leaves. Using thermal infrared imagery and the difference between the canopy and air temperatures (T c - Ta) used in Reference [18]; some studies use the canopy temperature directly [16, 22]. Using thermal infrared imagery and the crop water stress index (CWSI), used in References [18, 19, 21] is based on the difference between canopy temperature and air temperature (Tc - Ta), normalized by the vapour pressure deficit (VPD) [21]. A related variable, called Non Water Stress Baseline (NWSB), was also used in some investigations [23]. The rationale behind this is that water stress induces a decrease in stomatal conductance and less heat dissipation in plants, causing a detectable increase in the canopy temperature [16, 24]. Red-Green-Blue (RGB) images have been employed sparingly, usually associated with multispectral or thermal images for the calculation of hybrid variables such as the Water Deficit Index (WDI) [24]. Chlorophyll fluorescence, calculated using narrow-band multispectral images, has also been sporadically applied to the problem of water stress detection and monitoring [20, 25]. Nutrient status and deficiency monitoring: Plants need the appropriate levels of nutrients in order to thrive and produce a strong yield. The appropriate levels of nitrogen will ensure strong growth of vegetation and foliage, appropriate levels of phosphorous are required for strong root and stem growth and appropriate levels of potassium are necessary for improving of the resistance to disease and also to ensure a better quality of crop. If soil lacks any of these nutrients, the plant will become stressed and will struggle to thrive. NDVI Index mosaics offer the possibility to identify exactly which areas of the crops are stressed or struggling and to target directly these areas. The NIR/multispectral imagery provided by the UAVs can identify these management zones long before the problem become visible to the naked eye. This means that these management zones can be targeted before crop development and yield is affected. Currently, the most common way to determine the nutritional status is visually, by means of plant colour guides that do not allow quantitatively rigorous assessments [26]. More accurate evaluations require laboratorial leaf analyses, which are time consuming and require the application of specific methods for a correct interpretation of the data [27]. There are some indirect alternatives available for some nutrients, such as the chlorophyll meter (Soil-plant analyses development (SPAD) for nitrogen predictions [28], but this is a time consuming process [29] and the estimates are not always accurate [30]. Thus, considerable effort has been dedicated to the development of new methods for the detection and estimation of nutritional problems in plants [31]. Nitrogen is, by far, the most studied nutrient due to its connection to biomass and yield. Potassium and sodium [32]

have also received some attention. Multispectral images have been the predominant choice for the extraction of meaningful features and indices [33, 34], but RGB [35] and hyper spectral images [33] are also frequently adopted. Data fusion combining two or even three types of sensors (multispectral, RGB, and thermal) has also been investigated [35]. The vast majority of the studies found in the literature extracts vegetation indices (VI) from the images and relates them with nutrient content using a regression model (usually linear). Although less common, other types of variables have also been used to feed the regression models, such as the average reflectance spectra [32], selected spectral bands [34], colour features [36], and principal components [37]. All of

these are calculated from hyper spectral images, except the colour features, which are calculated from RGB images. Diseases monitoring Crop diseases can be devastating and classified as fungal, bacterial or viral. Drones equipped with Infrared cameras can see inside plants [38], giving a clear image of the condition thereof. If a farmer can detect an infection before it spreads, preventative measures can be taken - like removing the plant before the infection spreads to neighbour plants. Image-based tools can, thus, play an important role in detecting and recognizing plant diseases when human assessment is unsuitable, unreliable, or unavailable [39], especially with the extended coverage provided by UAVs. RGB [39, 40] and multispectral images [41, 42] have been preferred methods for acquiring information about the studied areas, but hyper spectral [43, 44] and thermal images [43, 44] have also been tested. The latter is employed mostly to detect water stress signs potentially caused by the targeted disease. Weed Control Weeds are not desirable plants, which grow in agricultural crops and can cause several problems. They are competing for available resources such as water or even space, causing losses to crop yields and in their growth. Yield losses due to weed in India: Rice (10-100%), Wheat (10-60%), Maize (3040%), Sugarcane (25-50%), Vegetables (30-40%), Jute (3070%), Potato (20-30%) etc. [45]. The use of herbicides is the dominant choice for weed control. In conventional farming, Farmers uprooted weeds after post emergence and the most common practice of weed management is to spray the same amounts of herbicides over the entire field, even within the weed-free areas. However, the overuse of herbicides can result in the evolution of herbicide-resistant weeds and it can affect the growth and yield of the crops. Using hyperspectral images to discriminate between the spectral signatures of some weeds with different resistances to glyphosate [46]. Using RGB sensors to classify various weed species [47]. Researchers used drone with hyper spectral sensors to monitor weed as a function of the plant canopy chlorophyll content and leaf density [48]. In addition, it poses a heavy pollution threat to the environment. To overcome the above problems site specific weed management is used to achieve this goal, it is necessary to generate an accurate weed cover map for precise spraying of herbicide. Drone can gather images and derive data from the whole field that can be used to generate a precise weed cover map depicting the spots where the chemicals are needed. Agro-drone application for weedicide spray useful for preemergence & post emergence weed control. Spraying is possible in any field condition (muddy, weeds, insects etc.) also in sunny and drizzling condition. Weedicide application

through drone is efficient and optimizes uses of weedicide. It is simple to use and easy to carry and maintain. Operate remotely that is very safe for health. Drone for Evapotranspiration (ET) estimation Evapotranspiration (ET) is an important process by which water is transferred from the land to the atmosphere by evaporation from the soil and by transpiration from living plants. Estimates of potential ET are used by professionals in the fields of hydrology, agriculture, and water management. Estimating evapotranspiration has been one of the most important researches in agriculture recently because of water scarcity, growing population, and climate change. Many kinds of unmanned aerial vehicles are used on different research purposes for ET estimation. Typically, there are three different UAV platforms, aircraft, fixed-wings, and quad copter. Aircraft is usually expensive, but it can fly longer and carry heavy sensors. Compared with aircraft, fixed-wings and quadcopter are less expensive. Fixed-wings can usually fly about 2 hours, which is suitable for a large scale of field. Quadcopter can fly about 30 minutes, which is used for short flight mission in a small scale of field. Being used as a remote sensing platform, UAVs also arouse new research problems, such as drone image processing, and flight path planning. A fixed-wing UAV to collect thermal data to estimate ET with two source energy balance models [49]. Evapotranspiration in a peach orchard estimated by using very-high-resolution imagery from an UAV platform (S1000, DJI, Shenzhen, China) [50]. A TIR camera (A65, FLIR Systems Inc.) and a multispectral camera RedEdge (MicaSense, Seattle, WA, USA) are also mounted on the drone. Multispectral and thermal images were collected by using an airborne digital system for estimation of evapotranspiration, developed by Utah State University [50]. The spectral bands for these cameras are, Red (0.645 µm - 0.655 µm), Green (0.545 µm – 0.555 µm), Blue (0.465 µm – 0.475 µm) and Near-infrared (NIR) (0.780 µm – 0.820 µm). A Thermal CAM SC640 (FLIR Systems Inc.) is also mounted on the aircraft to collect thermal infrared (TIR) images; the wavelength range is 7.5 µm – 13 µm. Compared with other satellites based remote sensing methods, UAV platform and light weight sensors can provide better quality, higher spatial and temporal resolution images [51]. Spraying Indian agriculture needed production and protection materials to achieve high productivity. Agriculture fertilizer and chemical frequently needed to kill insects and the growth of crops. Drones can be

used to spray chemicals like fertilizers, pesticides, etc. based on the spatial variability of the crops and field. The amount of chemicals to be sprayed can be adjusted depending upon the crop conditions, or the degree of severity of the insect-pest attack. The integration of UAV with sprayer system results a potential to provide a platform to pest management and vector control. This is accurate site specific application for a large crop fields. For this purpose heavy lift UAVs [52, 53] are required for large area of spraying. Researcher proposed the Quad copter (QC) system which is low cost, and lightweight, also known as Unmanned Aerial Vehicle (UAV) [54]. These quadcopter is small size, and this system can be used for indoor crops as well as outdoor crops. Quadcopter is an autonomous flight for spraying pesticides and fertilizer using the android device. Between the quadcopter and android device communication is done by Bluetooth device in real time operation. This system is used to

reduce agriculture field related problems, and also increases the yield of agriculture. The efficiency of the spraying system which is mounted to the UAV increases through the PWM controller [55, 56] in the pesticide applications. A blimp integrated quad copter aerial automated pesticide sprayer (AAPS) was developed for pesticide spraying based on the GPS coordinates in lower altitude environment [57]. To, overcome this low cost user flexible pesticide spraying drone “Freyr” was developed which is controlled by an android app [58] . A laboratory and field evolutions are analyzed for discharge and pressure rate of the liquid, spray uniformity and liquid loss, droplet density and sizes of a developed hexa copter mounted sprayer [59]. To reduce the wastage of pesticides an electrostatic sprayer introduced and designed on electrostatic spray technology with a hexa rotor UAV [60]. The WHO (World Health Organization) estimates there are more than 1 million pesticide cases every year. In that more than one lakh deaths each year, especially in developing countries due to the pesticides sprayed by a human being. The pesticide affects the nervous system of human and leads to disorders in the body. A remote controlled UAV (Unmanned Aerial Vehicle) is used to spray the Pesticide as well as fertilizer to avoid the humans from pesticide poison [61]. Crop dusting: Drones able to carry tanks of fertilizers and pesticides to spray crops with far more precision than a tractor. This helps reduce costs and potential pesticide exposure to workers who would have needed to spray those crops manually [62]. Pesticide application by drone can be used in all situations, especially in the places where labours are hard to find, environmental pollution can be reduced when it sprayed from lower altitude also it has a great potential to enhance pest management for small as well as the large crop field to entail highly accurate site-specification application [63]. Some scientist studied the impact of UAV (UAV N-3) spraying parameters at different working height and varying concentration of spraying pesticide on the wheat canopy and the prevention of powdery mildew in Asian countries [64]. This ultimately increases the efficiency of the chemicals applied, thereby reducing their adverse impacts on the environment by decreasing the soil and water pollution. Thus, it can lead towards sustainable agriculture. Drones spray chemicals at a faster rate as compared to other methods. It can also result in the saving of the amount of chemicals applied, which can reduce input cost. A major economic input for any agricultural season is the application of fertilizers (e.g., nitrogen, phosphate, potash), and micronutrients (e.g., sulphur, magnesium, zinc). Fertilizer is applied by on-ground equipment (tractor powered sprayers or pressurized irrigation systems) [65] or by manned aircraft [66] . The latter is the most preferred by producers with multiple and large land units. They generally use a single application rate for all fields being sprayed because changing wind speed and direction conditions during fertilizer application and the elevation of the aircraft make more precise application impossible. Ground equipment application is used as a complement to aerial spraying to maintain stable crop nutrient status across the irrigation season. UAV estimation of crop nutrient status can directly benefit the application rate recommendations by producer or agronomist consultant by including the entirety of the field. Research efforts indicate that it is possible to perform the monitoring with scientific UAVs and specialized camera sensors such as optical and thermal cameras [67, 68] along with specialized optical filters such as Red Edge or hyper spectral cameras [69, 70, 71]. Accelerometer and Gyroscope Sensors were used for spraying fertilizer and pesticide; it has ability to reduce time and human efforts [72].

Table 1: References dealing with the application of drones in various cases ~ 184 ~

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Application Water Stress Monitoring Nutrient Disorders Diseases Monitoring Weeding Evapotranspiration Spraying

Sensor/ model used Multispectral or Hyperspectral sensors and NDVI, GNDVI and PRI model Thermal infrared sensor and Canopy temperature, canopy temp.-Air temp. (Tc - Ta) RGB Sensor & WDI RGB, Multispectral and Hyperspectral sensors RGB sensor Multispectral images sensor Hyperspectral and thermal sensor Hyperspectral sensor RGB sensors Multispectral and thermal sensor GPS sensor Accelerometer and Gyroscope Sensors

Conclusion Drones have great potential to transform Indian agriculture. With the advancement of technology in the future, the production of drones is expected to become economical. The modern youth are not attracted towards farming due to hard work and drudgery involved in it. The implication of drones may fascinate and encourage the youth towards agriculture. Drones provide real time and high quality aerial imagery compared to satellite imagery over agricultural areas. Also, applications for localizing weeds and diseases, determining soil properties, detecting vegetation differences and the production of an accurate elevation models are currently possible with the help of drones. Drones will enable farmers to know more about their fields. Therefore, farmers will be assisted with producing more food while using fewer chemicals. Nearly all farmers who have made use of drones have achieved some form of benefit. They can make more efficient use of their land, exterminate pests before they destroy entire crops, adjust the soil quality to improve growth in problem areas, improve irrigation to plants suffering from heat stress and track fires before they get out of control. Therefore, drones may become part and parcel of agriculture in the future by helping farmers in managing their fields and resources in a better and sustainable way. Reference 1. Aditya S Natu, Kulkarni SC. Adoption and Utilization of Drones for Advanced Precision Farming: A Review. published in International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169. 2016; 4(5):563-565. 2. Zhang C, Kovacs JM. The application of small unmanned aerial systems for precision agriculture: a review. Precision agriculture, Springer. 2012; 13(6):693-712. 3. Everaerts J. The use of unmanned aerial vehicles (UAVs) for remote sensing and mapping. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2008; 37:1187-1192. 4. Colomina I, Molina P. “Unmanned aerial systems for photogrammetry and remote sensing: A review.”ISPRS Journal of Photogrammetry and Remote Sensing. 2014; 92:79-97. 5. Van Blyenburgh P. UAVs: an overview. Air & Space Europe. 1999; 1(5-6):43-47. 6. Bendig J, Bolten A, Bareth G. Introducing a low-cost mini-UAV for thermal-and multispectral-imaging. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2012; 39:345-349. 7. Anthony D, Elbaum S, Lorenz A, Detweiler C. On crop height estimation with UAVs. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2014), 2014, 4805-4812.

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Application of Drone Systems for Spraying Pesticides in Advanced Agriculture: A Review Ganesh P. Borikar1, Chaitanya Gharat2, Sachin R. Deshmukh3 1

School of Mechanical Engineering, Dr. Vishwanath Karad MIT World Peace University, Pune, India 2 School of Mechanical Engineering, Dr. Vishwanath Karad MIT World Peace University, Pune, India 3 School of Mechanical Engineering, Dr. Vishwanath Karad MIT World Peace University, Pune, India ganesh.borikar@mitwpu.edu.in , chaiatanyagharat10@gmail.com , sachin.deshmukh@mitwpu.edu.in Abstract. The farmers in agriculture fields face health problems due to diseases caused by pesticides and insecticides. Thousands of cases result in adverse health effects when spraying pesticides manually onto crop fields. The use of drones for spraying pesticides is a promising alternative to manual spraying. It represents a major emerging field in India. Therefore, this article is an attempt to explore the latest technological advances and applications in Hardware, Flight Controller (FC) & Electronic Speed Controller (ESC), Smart Agricultural Sensors, and Spraying Systems. To make a mention, a few key advancements in drone systems are: The crops can be monitored by the use of a multispectral camera, mounted on a drone. The drone spraying system makes use of GPS coordinates to auto-navigate GPS coordinates to spray the pesticides on the infected areas in real-time as soon as the camera takes a picture of the spraying area. Different types of nozzles are applied to lead to specific sprinkling speeds and adaption of Bluetooth Low Energy (BLE) via smartphone. Auto control of the quantity of pesticide as per the speed of the drone and use of Artificial Intelligence (AI) for smart drone path control. Along with challenges in spraying technology, the possible direction of future research is highlighted. These

technology upgrades lead to precision spraying, along with uniformity and less time. It could attract more and more farmers to spray pesticides by drone and increase crop yields in the coming years.

- Introduction In today's transforming world, the need for food resources has increased with the increasing population. With this increase in the food requirement, the demands from the agriculture sectors have increased tremendously. To fulfill this food demand and increase the food production rate, the agricultural sector needs to adopt automation that combines information and communication technologies (ICT), robotics, artificial intelligence (AI), big data, and the internet of things. This use of technology for increasing the food production rate to meet is called Smart Agriculture. Drones are one of the major technologies used in smart agriculture. Drones are unmanned aircraft, also called unmanned aerial vehicles (UAVs) in technical terms. In other terms, the drone is a robot that can be controlled remotely by a human or can fly autonomously, data acquired from sensors and other peripheral devices as well as commands from the mission planner. The drone is used for applications

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like search and rescue, monitoring, firefighting, surveillance, and agriculture, and the most common application is ariel photography [1]. Due to their great speed, accuracy, and effectiveness, drones are becoming more and more popular for carrying out different tasks [2]. Even the use of multiple drones for carrying out a similar task is possible which could reduce the time of completing the task [3]. In the history of drones, the United States, the United Kingdom, Russia, Germany, and Israel were the first countries to conduct research on drones. The first time an unmanned flying vehicle was used by the Austrians was in August of 1849. Charles Kettering, one of the first creators of drones in collaboration with Elmer Sperrym, Orville Wright, and Robert Milikanem created in 1915. They named the aircraft "Kettering Bug" which was automatic aircraft, which used to fly based on sensors barometer for height, the amount of engine spins for the calculating distance traveled, and the position [4]. Currently, drone technology is used to monitor real-time activities, manage disasters, provide security, and observe activities in the agriculture sector, mining sector, energy sector, and construction sector, among others [5]. With new upgrades coming up in drone technology it has stepped into performing different operations for various agriculture tasks. Talking about the use of drones in the agriculture sector it has a lot of applications which range from mapping and surveying to crop dusting and spraying [6]. So, in this article, reviews different types of drones, their working, different components used in drones especially concentrating on the crop spraying application using drones. 2. UAV Platforms Different types of drones have been used based on their application of use. Although they were used primarily for military functions, in the beginning, drones are expanding in different sectors of the industry. A drone is classified according to its size, range, ability, and weight. Drones can be classified into two main types: fixed-wing drones and rotary-wing drones [7].

Figure 1. Type of Drones

Figure 2. Type of drones (a) Fixed Wing Drone, (b) Single Rotor drone, (c) Multi-Rotor

2.1. Fixed-wing drone The rigid streamlined wing structure of a fixed-wing drone (Fig. 2 (a)) induces lift as it moves [8]. It completely looks like a normal aircraft but without a pilot on board. It consists of one or two I.C. engines or an electric motor attached with a propellor that generates the forward thrust. The drone wings are made with a specific airfoil which generated an air pressure difference from the front surface of the airfoil to the end surface of the airfoil. The ailerons, elevators, and rudders installed on the drone's wings are used to regulate its movement. Drones with fixed wings are advantageous

because they can fly long distances, reach high altitudes, and operate quietly. They are used mostly for surveillance. 2.2. Rotary-wing drone Rotary wing drones are those that generate lift by rotating blades called propellers [8]. Single Rotor Drones and Multi-Rotor Drones are the two types of Rotary Wing Drones. The Single Rotor Drones (Fig 2 (b)) are similar to helicopters in that they have a single rotor. They are mostly used in the construction industry for surveillance. Multi-rotor drones, on the other hand, are the most common form of drone in the market. The multirotor drone generates propulsion and manoeuvres by simply changing the speed of individual rotors with the help of a flight controller. The number of rotors on a Multi- Rotor Drone is categorised as follows: Tricopter (fig 3 (a)), Quadcopter (fig 3 (b)), Hexacopter (fig 3 (c)), and Octocopter (fig 3 (d)). The quadcopter is by far the most common type of multi-copter. They are commonly used in real-time monitoring, surveillance, mapping, etc. but the main application of multirotor drones is seen in aerial photography for beautiful cinematic videos.

(a)

(c)

(b)

(d)

Figure 3. Multi rotor Drone (a) Tricopter, (b) Quadcopter, (c) Hexacopter,(d) Octacopter [38] 3. Working Principle Each type of drone discussed above have their working principles but for this article, we will be concentrating mainly on the working principle of the Quadcopter. A quadcopter has 4 rotors that are equally spaced from each other with a definite circular wheelbase on the drone frame. Drone use BLDC motors and the propellor blades are attached to the cover of the motor. The propellor blades are the most important part of the drone because they help the drone to generate proper amount of thrust which is the lift force for the drone. The blades are so designed that the lift force generated will be in the same direction on both parts of the blades. A flight controller along with the ESC controls the motor speed. The greater the motor speed (Blade speed) the greater will be the lift force. Now comes the question of how the drone will take off. The lift force increases as the rotor speed increases, and when the lift force overcomes the weight of the drone, it is referred to as climbing. When the drone reaches a sufficient altitude, we reduce the rotor speed until the lift force equals the drone's weight, and the drone begins to hover in the air, which is known as drone hovering in technical terms. All four rotors rotate at the same pace while hovering and climbing. Now the other question arises how does the drone move forward, sideways, and spin? Talking about moving forward, forward pitch (fig 4 (a)) is achieved when front propellors are spun at lower speed and the back propellor at higher speed. The drone's weight is balanced by the vertical component of the lift force, while the imbalanced horizontal force causes the drone to fly forward, causing a drag force on the body. The horizontal force must be increased until it matched the drag force for attaining constant speed. The same is the case for pitching backward. The same goes for rolling (fig 4 (b)) but here the side pair is spun faster than the opposite side pair. To yaw (fig 4 (c)) means to spin the drone the diagonal rotor spun at a different speed than the other diagonal rotors.

3

Figure 4. Movement of drone (a) Pitch, (b) Roll, (c) Yaw

- Components of the Drone A drone is made up of many different components which are interconnected to each other. But the key components necessary for a drone to work are a flight controller (Fig 6 (a)), BLDC Motors (Fig 6 (b)), ESC's (Fig 6 (c)), propellors (Fig 6 (d)), battery (Fig 6 (e)), and a radio controller (Fig 6 (f)). The drone's brain is referred to as a flight controller. The flight controller receives data from the humancontrolled radio transmitter as well as sensors onboard. The controller then processes the information and sends commands to the ESCs, which control the motor's speed. The ESCs are attached to the

power distribution board (the battery), and the flight controller receives signals from the ESCs, which govern the power delivered to each of the motors. The primary BLDC motors are used in drones. These motors are responsible for rotational motion. The propellers are connected with the motors which convert the rotational motion of the motors into thrust force which is required for lifting the drone in the air. For all these components to work we need an energy source which is the battery. The battery supplies the electric energy required to each component of the drone. The battery used in the drone is mostly LIPO batteries. Additionally, the drone also consists of two more components which are the accelerometer and the gyroscope. Because the accelerometer monitors both acceleration and force, the descending gravity will be detected as well. We can determine the device's orientation using the accelerometer's three-axis sensors. A gyroscope is a device that monitors angular velocity, or rotational speed around the three axes. A gyroscope is a gadget that helps determine orientation by using Earth's gravity. A freely revolving disc known as a rotor is attached to a spinning axis in the middle of a bigger and more stable rotor [9].

Figure 5. Drone Components (a) Flight controller, (b) BLDC Motors, (c) ESC, (d) Propellors, (e) Battery, (f) Radio Transmitter and Receiver [40] 5. Drone Control Approach Drones are controlled with two different approaches either manually or autonomously. The manual approach relies on the commands given by humans in real-time by the use of transmitters like radio transmitters [10], Bluetooth, or Wi-Fi. The signal from the transmitter is received by the drone's receiver, which then delivers it to the flight controller for additional processing. The Autonomous approach does not depend on the real-time control commands from the human but it follows the pre-specified instructions given by the human in the mission planning software. The commands consist of path plan, speed limit, altitude range, etc. The drone operates autonomously without human intervention and does the given task by following the instructions. The different flight controllers with their controlling approaches are given in the table below (Table 1).

Table 1. Flight controller with control approach Flight controller

Control Approach

References

NAZA M-lite flight controller

Radio Transmitter

[1]

ATmega328

Radio Transmitter

[3][18][28]

Arduino mega APM Ardupilot controller

Wi-Fi Radio Transmitter

[2] [10]

Pixhawk controller

Autonomous

[22][23][32]

KK 2.1.5

Radio Transmitter

[25][26][31]

Raspberry Pi Model 3 B

Autonomous

[36]

- Recent Trends and Challenges The drone is increasingly being used in the agricultural sector with technological advancement. These help in reducing the efforts of farmers and also on other hand providing more accuracy and fast operation. The drone is nowadays used in various fields of agriculture works like crop monitoring, seeding, spraying of insecticides and pesticides, and irrigation [11-13]. The predominant use of drone today in agricultural sector is spraying of pesticides. Details of the drones used by various users in recent time for pesticides spraying along with their technical elements are listed below in Table 2. Table 2. Existing drones for spraying pesticides in recent time Exiting Drones

Max. Speed

Discharge rate

No. of nozzles

Reference

Volume of pesticide

Max. Flight time full load

DJI Agrus MG-1S

10 L

10 min

12 m/s

0.379 L/min

4

[38]

3WQF120-12

12 L

30 min

5 m/s

0.8 L/min

2

[39]

3CD-15

15 L

20 min

6 m/s

0.54 L/min

4

[39]

WSZ-0610

10 L

20 min

4 m/s

0.72 L/min

2

[39]

HY-B-15L

15 L

15 min

4.5 m/s

0.38 L/min

5

[39]

N-3 UAV

25 L

-

4 m/s

0.85 L/min

2

[40]

Knapsack-type electric fog sprayer 3WBD

20 L

-

1m/s

1 L/min

1

[40]

Along with the benefits of drones, there are some challenges in agricultural drones. They are like less flight time, balancing of drone with the pesticide tank, harsh weather conditions, etc. The most important challenge is the flight time of the drone, due to the relatively higher payload. The flight time of the drones used in agriculture is short, which ranges from 10-30 minutes which leads to less coverage of land with every charge. The other challenge is that for large area of spraying, drones are less efficient and they are costlier than the other equipment used for the same purpose.

5

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- Drone for Crop Spraying The drone has a wide range of applications in various sectors for different industries and hence it also has some appearance in the agriculture sector. The drone can serve the agriculture sector right from surveying and monitoring the field and crop to spraying of pesticides and seeds on the field. The main problem faced while growing crops are pests and weeds. They tend to damage the crop, which results in loss of money, time, and efforts in a short loss in productivity [14]. To kill pest and weeds, herbicides and fertilizers must be used. However, the WHO (World Health Organization) estimates that over 1 million pesticide cases occur each year. More than one lakh people die each year as a result of pesticides sprayed by humans and pesticide handling, primarily in developing countries [20]. As a result, hand fertilizer and pesticide spraying might result in lethal diseases such as cancer, asthma, hypersensitivity, and other disorders [14-20]. Here's where we'll be able to use the drones. Crop monitoring, as well as the need to spray pesticides and fertilizers at precise plant locations, is a crucial component for increasing crop output. The Drones can complete the task fast and accurately without giving any health

hazards to humans. The drones used in agriculture sectors are majorly autonomous drones, which decides by themselves by sensing the surrounding and considering the task allotted to them by the human. The Pesticide spraying drones typically have a storage tank in the lower section of the drone that holds the liquid pesticide, and nozzles are connected to the storage tank through pipes and an electric pressure pump to spray the pesticides down on the crops. The storage tank, nozzle, and pressure pump work in one of two ways: manually with a controller or automatically with previously programmed commands for spraying pesticides at precise spots. The following table lists the spraying systems details /components used in pesticide spraying drones (Table 3). Table 3. Various types of spraying systems used in drones Tank capacity (liter)

Nozzle type

5 litres

Flat fan

5.7 L -

Micronair nozzles The Universal nozzle

Pump discharge

Reference

2.5 L/min

[17]

100 mL/min 1 L/min

[19] [20]

10 L

XR11001

0.43 L/min

[21]

13.2 L

flat fan nozzles

46.8 L/ha

[24]

6L

flat fan nozzles

2.5 L/min

[25]

250ml 5L

-

250 mL/min 2.4 L/min

[31] [35]

- Conclusions There is a vast scope for using drones in agricultural applications. They can be used from soil monitoring and surveying to sprinkling of seeds and pesticides. However, there are some limitations and challenges to overcome. This article briefly summarize pesticide spraying drone systems /various components. It specified various drone platforms, control approaches, and agricultural UAV applications that have been established or are currently being researched. The use of different controlling approaches has been discussed according to their application. It highlights the need to minimize pesticide spraying drone weight, maximize drone flight time and more precise autonomous control of drone.

6

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A review on the use of drones for precision agriculture Pasquale Daponte, Luca De Vito, Luigi Glielmo, Luigi Iannelli, Davide Liuzza, Francesco Picariello and Giuseppe Silano Department of Engineering, University of Sannio, Piazza Roma, 21, 82100 Benevento, Italy E-mail: {daponte, devito, glielmo, luigi.iannelli, davide.liuzza, fpicariello, giuseppe.silano}@unisannio.it Abstract. In recent years, there has been a strong activity in the so-called precision agriculture, particularly the monitoring aspect, not only to improve productivity, but also to meet demand of a growing population. At a large scale, precise monitoring of cultivated fields is a quite challenging task. Therefore, this paper aims to propose a survey on techniques, applied to precision agriculture monitoring, through the use of drones equipped with multispectral, thermal and visible cameras. For each application, the main limitations are highlighted and the parameters to be considered before to perform a flight are reported.

- Introduction Farming is facing many economic challenges in terms of productivity and cost-effectiveness, and the increasing labour shortage partly due to the depopulation of rural areas, as well. Among such global challenges, it should be considered the population increase, the urbanization, an increasingly degraded environment, an increasing trend toward consumption of animal proteins changing in food preferences through aging population and migration, and, of course, the climate change [1, 2]. Furthermore, reliable detection, accurate identification and proper quantification of pathogens and other factors affecting both plant and animal health, are critical to be kept under control in order to reduce economic expenditures, trade disruptions and even human health risks. Thus, a more advanced agriculture needs to be set, characterized by the adoption of ad hoc production processes, technologies and tools derived from scientific advances, research and development activities. Precision farming and measurements have already established paradigms in order to increase farm productivity and quality, as well as improving working conditions through reduction of manual labour. All these factors play an important role in making farming sustainable. Also, many modern farmers already use high-tech solutions, e.g., digitally-controlled farm plants and also unmanned aerial vehicles (UAVs) for monitoring and forecasting. Drones are available at affordable prices and are capable of imaging ground data with corresponding geographic locations. That helps the user to have a complete and clearer picture of the ground information. For instance, multispectral and RGB cameras equipped drones offer the advantage of imaging the near infrared portion of the electromagnetic spectrum over the crops, thus providing the crops health conditions [3]. Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI. Published under licence by IOP Publishing Ltd 1

Figure 1. Pre-programmed navigation trajectory for the soil assessment in the APM Planner open-source software. Drone images and ground sensor data are so expected to play a crucial role in precision agriculture, providing wide room for scientific research and development [4]. Furthermore, several metrological aspects have to be considered for developing such platforms, from the sensors embedded on them up to the instrumentation and the calibration procedures for their testing [5]. Despite their effectiveness and usefulness, the main drawback lies on the fact that these systems are calibrated only for a specific task (e.g., classifying different kinds of vegetation, water bodies, urban, bare soil, etc.), without the ability of creating a holistic view of agricultural processes. This lack of interoperability causes additional work for the human operators, since they have to manually feed the output data from one system to another. For all such reasons, software modules, drones and other equipment are object of research in order to develop a common information middleware and application interface. The aim is to reduce monotonous and time consuming work [6]. In this paper, a review of the drone technology applied to the precision agriculture is presented. In particular, the drone architecture according to the sensors embedded on the payload for precision agriculture applications is reported. Then, the design of a drone in terms of measurements capabilities, power consumption and time of flight according to the application requirements is delineated. Emphasis is also placed in the control part of the drone, understanding its dynamic behavior and how to control it. In such a way, changes in the decision-making system and the mission planner can be made in a simpler way, facilitating the development of different control strategies compared to those already available and validating the effects of modifying the control architecture for complex missions. Finally, the main procedures needed for the calibration of the sensors embedded on drones are reported and an overview of the post-processing tools for extrapolating significant parameters of the monitored area are described. The rest of the paper is organized as follows. An overview of the drone architectures and the payload sensors for precision agriculture together with its flight control system are reported in Sec. 2 and 3, respectively. Section 4 describes the use of drones for precise agriculture and, for each application, a review of the needed calibration procedures is carried out. Moreover, the main post-processing tools are described. Finally, Section 5 concludes the paper. 2. The architecture of a drone for precision agriculture As reported in [7], the basic architecture of a drone, without considering the payload sensors, consists of: (i) frame, (ii) brush-less motors, (iii) Electronic Speed Control (ESC) modules, (iv) a control board, (v) an Inertial Navigation System (INS), and (vi) transmitter and receiver

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Figure 2. Architectural overview of the Parrot Bluegrass. modules. In precision agriculture, as well as in disaster relief, building inspection or traffic monitoring, the employed drones are semi-autonomous. In that case, the drone has to fly according to the definition of a flight path in terms of waypoints and flight altitude. Thus, the drone has to embed on board a positioning measurement system (e.g., Global Navigation Satellite System, GNSS) for knowing its position with respect to the waypoints. Furthermore, it embeds an altimeter (e.g., barometer, laser altimeter, ultrasonic sensor) for flying at constant flight altitudes. An example of software for defining the mission trajectory is the APM Planner [8]. In Fig. 1, the user interface of this tool is depicted. The payload of a drone includes all the sensors and actuators that are not used for the control of its flight (e.g., the gimbal with the RGB camera). In case of precision agriculture, the sensors embedded on drones are: multispectral camera, thermal camera, RGB camera and Light Detection and Ranging (LiDAR) systems. Multispectral cameras are used for quantifying the state of the monitored vegetation in terms of: (i) chlorophyll content, (ii) leaf water content, (iii) ground cover and Leaf Area Index (LAI), and (iv) the Normalized Difference Vegetation Index (NDVI). Thermal cameras have demonstrated high potential for the detection of water stress in crops due to the increased temperature of the stressed vegetation. For example, in [9], the authors propose a drone for vegetation monitoring using thermal and multispectral cameras. The thermal camera is the thermovision A40M, with 320 × 240 pixels and having a spectral response in the range of 7.5 μm to 13 μm. Furthermore, each pixel has a resolution of 16 bits and a dynamic range of 233 K to 393 K. The multispectral sensor is the six-band multispectral camera MCA-6 Tetracam. The camera consists of six independent image sensors and optics with user configurable filters, having center wavelengths at 490, 550, 670, 700, 750, and 800

nm, respectively. RGB cameras and LiDAR systems are usually adopted to digitize the terrain surface to provide the Digital Terrain Model (DTM) or the Digital Surface Model (DSM) of the monitored area. The DSM represents the earth's surface and includes all the objects on it. On the other hand, the DTM represents the ground level of the soil without considering the vegetation height. For example in [10], the authors use the Swinglet CAM drone with embedded the compact camera Canon IXUS 220 HS for estimating the characteristics of a vineyard. They have performed a flight by acquiring the images related to a vineyard in several waypoints. By using the commercial tool Pix4Dmapper [11], the DSM and DTM are extrapolated. In particular, the differential model of the vine rows is obtained by subtracting the DTM from the DSM. According to the previous examples, in order to use a drone for precision agriculture, at least the following capabilities are needed: (i) the drone has to fly according to waypoints definition,

xr , yr , zr , ψr xd , yd , zd , ψk

Reference θc , φc On-board ω1 , ω2 Generator Ωc , ψ̇c Control ω3 , ω4 pk qk rk

ud vd

Figure 3. The control scheme. Subscript c indicates the commands, r indicates the references, d indicates the drone variables and k indicates the sensors and data fusion outputs. (ii) the drone has to control its flight altitude, (iii) the drone has to sense and avoid obstacles during the flight, (iv) the drone has to land according to the state of the battery, automatically and (v) the acquired images have to be stabilized with a gimbal. An example of drone that can be used for precision agriculture and fulfills the above mentioned requirements is the Parrot Bluegrass (see, Fig. 2). In particular, it can be driven according to preliminary defined waypoints and flight altitude values. Furthermore, it embeds a RGB camera, the Parrot Sequoia multispectral sensor and a sensor for measuring the environmental luminosity. 3. Flight control system As a common rule in the literature [12, 13], the flight control system of semi-autonomous drones is split into two parts: a reference generator (outer loop), that takes into account the position to reach, expressed in terms of waypoint (xr , yr and ψr) and flight altitude (zr), and generates the command signals (ψ̇c , Ωc , θc and φc); and an on-board control system (inner loop), that uses such commands providing as output the motors speed ωi (i from 1 to the number of propellers). They work together in a cascade control structure, where the inner loop (on-board) needs to regulate at a rate faster than the outer loop (that usually runs on a ground control station). Figures 3 and 5 describe the overall system and the on-board control architecture, respectively. The reference generator uses the drone position (xd , yd and zd) and the orientation along zaxis (ψk) to compute the command signals (ψ̇c , Ωc , θc and φc), where the drone position and velocity (ud , vd and wd) come from the positioning measurement system. There are many approaches to carry out the references, from basic heuristic techniques to more advanced model based methods that exploit an accurate dynamical model of the plant. However also classical (and simple) Proportional Integral Derivative (PID) controllers might benefit from a detailed model. In any case, the dynamical model of the aircraft can be easily derived by introducing the so-called inertial (OFI) and body (OABC) reference systems, as depicted in Fig. 4. Further details can be found in [12, 13]. The aim of the reference generator is to reach the position coordinates (xr , yr , zr and ψr) by tuning the desired attitude (θc and φc), the heading velocity (ψ̇c) and the thrust (Ωc) of the drone, later used as references for the on-board control system. Usually, it is not much complicated to design or modify the available control architecture. For example, in the case of the Parrot Bluegrass, the Software Development Kit (SDK) can be employed to implement a suitable position controller improving the performance of the existing one in the mission planner. Also, the on-board control is decomposed into two parts: the attitude and the rate controller, both illustrated in Fig. 5. The scheme integrates the state estimator that, starting from the accelerometer and gyroscope data, allows to estimate the attitude (ψk , θk and φk) and the angular velocities (pk , qk and rk) of the drone, used by the on-board control loop. Usually, such control architecture is "closed", especially when using commercial applications. Therefore, it is not possible to make changes to either the control gains or the control loop (state estimator included). Thus, those drawbacks and limitations have to be considered when going to design a flight control system in a precision agriculture scenario. Disturbances rejection in adverse 4

ez ψ ω2 ω3 ω1

OABC ω4

θ ey

φ ex

Z

OF I

X

Y

Figure 4. Drone in the body-frame (OABC) and the fixed-frame (OFI) reference system. The forces, the spin direction and the propellers velocity, ωi , from each rotor are also reported. ψ̇c θ c , φc + − θk φ k

Attitude PID

Ωc

• pc + qc − p k qk rk

Rate PID Controller

Actuators (motors) Gyroscope

Sensor Fusion

Accelerometer

Aircraft

Figure 5. On-board control architecture of a semi-autonomous drone. Usually, the attitude controller runs at 250 Hz while the rate controller runs at 500 Hz. weather conditions and robustness against model uncertainties are a key feature. Indeed, the aircraft has to be able to control its position under the influence of wind gusts. This is especially true when flying close to obstacles (e.g., threes or vineyards), since position errors due to a wind gust might cause a collision damaging the crops. Current position control methods, such as PID, do not perform well under the influence of gusts. Indeed, PID gust rejection properties scale with magnitudes of the gains, which is often limited by the positioning measurement system update frequency in outdoor scenarios. Moreover, the integrator term is generally slow in compensating persistent wind disturbances. Nowadays, there is much activity of the scientific research in this specific field [14, 15].

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Figure 6. The post processing procedure for extrapolating information related to the state of the vegetation from the acquired multispectral images.

Figure 7. The monitoring operations of a crop by means of multispectral camera embedded on drone. 4. The use of drone for precision agriculture Intensive agriculture has several negative impacts on the environment. It adds significant and environmentally detrimental amounts of nitrogen and phosphorus to terrestrial ecosystems [16]. Also, excessive fertilizers application can cause pollution risks for the environment, whereas insufficient fertilizer used to replace nitrogen and phosphorus lost through intensive cropping can lead to soil degradation and loss of fertility. Additionally, pollution of water courses and bodies, and consequent degradation of water-related ecosystems are rising due to agricultural chemicals seeping into nearby water. Furthermore, serious soil degradation, which threatens the productivity of the different soils, can be observed all over Europe [17].

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Figure 8. The 3D reconstruction process by considering two images acquired by drone in two waypoints [22]. In addition to the environmental impact, the health risk aspect of the use of chemicals in agriculture needs to be considered. Indeed, chemicals may threat farm workers, as well as families and possibly the inhabitants of the areas surrounding crops, vineyards and farming sites. Additionally, pesticides are absorbed by crop and natural resources (i.e., water and soil) and end up as concealed substances in the food chain, with the increasing risk for both livestock and humans, with huge negative impacts on the public health. Through autonomous precision farming, these effects can be mitigated since chemicals, such as fertilizer and pesticides, are only administered where needed instead of being applied over a large area. In such a context, the use of drones in agriculture has recently been introduced for big areas inspection and smart targeted irrigation and fertilization [18, 19]. The possibility of detecting, by a drone and an infrared camera, the areas where a major irrigation is needed or where a foliage disease is spreading, can help agronomists to save time, water resources and reduce agrochemical products. At the same time, such advanced farming techniques may lead to increased crop productivity and quality. Specifically, water deficiency, nutrient stress or diseases can be localized and measured and decision can be made to fix the problem. Many vegetation indexes have been developed which involve various data features, such as the NDVI. Special camera systems are able to acquire data from an invisible part of the electromagnetic spectrum called Near-Infraed (NIR) and extract quality information, such as the presence of algae in the rivers or oil spills near costs [20]. Current agriculture drones applications [21] are: (i) biomasses, crop growth and food quality monitoring, (ii) precision farming, such as to determine the degree of weeds for site-specific herbicide applications, (iii) harvesting and logistic optimization. All these applications require the processing of the images acquired from a camera embedded on the drone. According to the sensors embedded on drones, it is possible to define three types of applications for precision agriculture: (i) applications based on multispectral and thermal cameras, and (ii) applications based on RGB cameras.

Figure 9. Height uncertainty value uh vs flight altitude and pitch angle uncertainty value uθ , for different uncertainty values related to the measurement of the distance between the two waypoints [22]. 4.1. Applications based on multispectral and thermal cameras Usually, for agriculture the terrain is scanned by using satellites with multispectral and thermal cameras. For precision agriculture, due to the needed high spatial resolution, drones are more suitable platforms than satellites for scanning. They offer much greater flexibility in mission planning than satellites. The drone multispectral and thermal sensors simultaneously sample spectral wavebands over a large area in a ground-based scene (see, Fig. 7). After post-processing, each pixel in the resulting image contains a sampled spectral measurement of the reflectance, which can be interpreted to identify the material present in the scene. In precision agriculture, from the reflectance measurements, it is possible to quantify the chlorophyll absorption, pesticides absorption, water deficiency, nutrient stress or diseases. There are four sampling operations involved in the collection of spectral image data: spatial, spectral, radiometric, and temporal. The spatial sampling corresponds to the Ground Sample Distance (GSD). The GSD is the distance in meters between two consecutive pixel centers measured on the ground. It depends on the sensor aperture and the flight altitude. The spectral sampling is performed by decomposing the radiance received in each spatial pixel into a finite number of wavebands. The radiometric resolution corresponds to the resolution of the Analog to Digital Converter (ADC) used for sampling the radiance measured in each spectral channel. Furthermore, the temporal sampling refers to the process of collecting multiple spectral images of the same scene in different instants. Those four sampling operations have to be taken into account for the design of a flight mission and for choosing correctly the multispectral camera and the drone platform. The postprocessing procedure required for extrapolating information from the acquired multispectral and thermal images is depicted in Fig. 6. In particular, the images acquired by drone provides measurements related to the radiance in each pixel. In order to measure the reflectance, image processing algorithm are applied to compensate the effects due to the atmosphere absorption and the spectrum of the solar illumination. From the reflectance values, it is possible to detect several materials and the state of the vegetation according to known spectral responses.

4.2. Applications based on RGB cameras In precision agriculture, the images acquired by drones embedding RGB cameras are used for extrapolating DTM and DSM related to the surveyed area. To this aim, it is important to define the flight mission parameters according to the spatial resolution, and the measurement accuracy of the reconstructed DTM and DSM. As in case of multispectral and thermal cameras, the spatial resolution is defined in terms of GSD. According to the GSD that would be reached, the camera resolution and the flight altitude are chosen. The height measurements of the terrain and of the objects in the scene are obtained by taking two consecutive images from the camera in two different waypoints [22]. The two images have to overlap the same objects in scene (see, Fig. 8). Usually, an overlapping factor of the 70 % between the two images is adopted. From the two acquired images, by knowing the camera parameters, the position and the altitude of the waypoints, it is possible to extrapolate the heights of the objects in the scene. In [22], the authors propose an uncertainty model for quantifying the accuracy related to the 3D reconstruction of a terrain or a surface by means of aerial photogrammetry. As reported in Fig. 9, they have modeled the uncertainty related to the height measurements for several flight altitudes according to the uncertainty on the measurements of the distance between two waypoints and the orientation of the second waypoint respect to the first one. From that figure, it is possible to observe that the uncertainty on the height measurements at a flight altitude of 16 m is in the order of 30 cm. Furthermore, they have evaluated the uncertainty related to the commercial tool, Pix4Dmapper [11], adopted to provide DTM and DSM. In that case, at the flight altitude of 11 m, the measurement uncertainty is 30 cm. From those analyses, it is highlighted that the accuracy related to a 3D reconstruction mainly depends on the accuracy of the drone position measurement system. Thus, according to the target accuracy, several techniques for localizing the drone during the flight can be adopted: (i) differential GPS systems, having a position accuracy in the order of 1 m, (ii) real-time kinematic (RTK) GPS, having an accuracy in the order of 2 cm, and (iii) simultaneous localization and mapping (SLAM) based techniques achieving a position accuracy in the order of 10 cm. 5. Conclusions In this paper, a review on the use of drones for precision agriculture has been presented. In particular, the general architecture of a drone for multispectral/thermal sensing and DTM/DSM has been discussed. Some technical details about the control system architecture have been also provided. Furthermore, for both the applications, the main limitations and the parameters to take into account before performing a flight are described. Future trends in this research field go toward the use of cheap commercial mini or micro drones. However, in doing so, the measurement accuracy specifications are challenging to be addressed and several problems arise. For example, for that drones the wind influence, the low GPS accuracy and the strong drift of the INS play destructing effects in flight stability and image acquisition [23]. 6. Acknowledgements This work was partially funded by European Commission H2020 Framework Program under Grant No. 783221 - AFarCloud project - “Aggregate Farming in the Cloud”. References [1] Gnip P, Charvat K and Krocan M 2008 Analysis of external drivers for agriculture World conference on agricultural information and IT, LAAID AFITA WCCA 797–801 [2] Carpenter S R, Caraco N F, Correll D L, Howarth R W, Sharpley A N and Smith V H 1998 Nonpoint pollution of surface waters with phosphorus and nitrogen Ecological Applications 8 559–568 [3] Reinecke M and Prinsloo T 2017 The influence of drone monitoring on crop health and harvest size 2017 1st International Conference on Next Generation Computing Applications pp 5–10

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Drone-PPT-CIB-RC

Slide 1

Critical issues involved in pesticide application using Kisan drone and future roadmap

Government of India

Ministry of Agriculture and Farmers Welfare

Department of Agriculture and Farmers Welfare

Directorate of Plant Protection, Quarantine & Storage

Central Insecticides Board & Registration Committee

N.H.IV., Faridabad-121001

Slide 2

STATUTORY COMPLIANCES

Marking of the area shall be the responsibility of the operators

The operators shall use only approved insecticides and their formulations at approved concentration and height;

Washing decontamination and first-aid facilities shall be provided by the operators

All aerial operations shall be notified to the public not less than twenty-four hours in advance through competent authorities.

Animals and persons not connected with the operations shall be prevented from entering such areas for a specific period

The pilots shall undergo specialization training including clinical effects of the insecticides.

As per provision envisaged under the Insecticide Rules 1971, Chapter VIII Rule 43 on Aerial Spraying Operations, the aerial application of Insecticide (pesticides) shall be applicable for pesticide application through drones subject to the following provisions:

Slide 3

Standard Operating Procedure (SOP) on use of drone for crop protection covers

- Statutory provisions explained (Point No 2 of SOP)
- Detail precautions for drone-based pesticides application (Point no 4 of SOP)

pre-application requirements

requirements while undertaking pesticide application

post-application requirements

- Critical parameters (Point No 5.2 of SOP)
- Environment limitations of drone use (Point No 5.3 of SOP)
- Pilot Training (Point No 5.4 of SOP)
- Drift Management (Point No 5.5 of SOP)
- Safeguarding the non-targets (Point No 5.6 of SOP)
- Registration requirements of pesticide for drone application (Point No 6 of SOP)
- Spray Monitoring form and data submission (Point No 7 of SOP)

Slide 4

Requirements while using Drone

Pre-application:

Confirm not to fly in the drone-forbidden area (airport or electronic station). No prior permission is required for operating an unmanned aircraft system in a green zone.

Ensure your Drone is Digital Sky Compliant with , “No Permission – No Takeoff” hardware and firmware

Obtain Unique Identification Number (UIN) from DGCA for operating in controlled airspace and affix it on your drone.

Obtain Unmanned Aircraft Operator Permit (UAOP), if applicable from DGCA

Keep an eye on interference: Interference can be from mobile devices or blockage of signals, do watch out when flying your drone.

Ensure the operators are trained on both drone operation and safe use pesticide.

No alcoholic drinks should be consumed within 8 hours preceding operation.

Calibrate drone spray system to ensure nozzle output and accurate application of labeled rates.

Slide 5

Set up the least buffer zone (as specified by DGCA/ CIB&RC) between drone treatment and the non-target crop.

Confirm presence of water sources - Do not spray pesticides near water sources (less than 100 m from target area) to avoid polluting water sources.

Do log your flights and intimate concerned authorities (like DGCA, local police etc.)of any incidents/ accidents .

Don't fly drone over groups of people, public events, or stadiums full of people without permission.

Don't fly drone over government facilities/military bases or over/ near any no-drone zones.

Don't fly drone over private property unless permission is given.

Don't fly drone in controlled airspace near airports without filing flight plan or AAI/ADC permission (at least 24 hours before actual operation).

Don't fly drone from a moving vehicle, ship or aircraft.

Don't fly the Drone in contraventions to the Unmanned Aircraft System Rules (UAS), 2021 rules as published by Ministry of Civil Aviation vide G.S.R. 589(E) dated 25thAugust, 2021and as amended from time to time.

Slide 6

During Application:

Read labels carefully to understand safety guidance

Wear Personal Protect Equipment (PPE).

Do not eat, drink or smoke while spraying

Confirm the flying route was reasonable to minimize turn around.

Spray with pure water first to test operation for at least 5 minutes wherever feasible and required.

Ensure two-step dilutions to fully dissolve the pesticide

Adopt proper pressure for optimized droplet spectrum (>100µm).

Check weather conditions for:

a. Appropriate Wind speed,

b. Appropriate Temperature,

c. Appropriate Humidity

Ensure appropriate flying height above target crop.

Ensure appropriate water volume.

Slide 7

Ensure appropriate flying speed.

Avoid walking through treated areas.

Do not spray during the active bee foraging period. Avoid spray drift to flowering crops

When spraying pesticides that are toxic to non-target organisms viz; fish, birds and silkworm, strictly abide by the product label requirements and take effective measures to avoid risks.

Avoid drift to ensure safety for humans, animals and the environment

Slide 8

Post Treatment:

Timely evacuation and transfer to fresh air.

Never burn or bury hazardous waste.

Never leave empty containers in the field. It should be disposed of as per the Insecticides Rule 1971.

Set up warning signs in the spray area for reminding people.

Take a shower and put on clean clothes

Slide 9

Critical parameters to be considered for Drone-based pesticide application:

Pesticides/Insecticides:

Only Central Insecticides Board and Registration Committee (CIB&RC) approved Pesticides/Insecticides shall be used.

The dose has to remain within the range approved by CIB&RC.

Pesticides/Insecticides should be diluted only with clean water wherever applicable or with another suitable ingredient as approved by the CIB&RC.

Slide 10

Registration requirements of pesticides for drone application:

The Registration requirements of pesticides for drone application and the modalities are dynamic in nature and will be considered based upon the safety, efficacy, statutory and legal requirements and published by the Central Insecticides Board and Registration committee (CIB&RC) from time to time.

Drone users shall use only Central Insecticides Board and Registration Committee approved pesticides.

For registration of insecticides/pesticides and for use with drone, the applicant shall apply before Secretariat of CIB&RC, in the manner, as prescribed by CIB&RC under the Insecticides Act, 1968.

Slide 11

Data requirements:

To endorse the use of Drones as alternate/additional spraying equipment

or

Product with existing label claim expansion with the use of sprayers and Drones as spraying equipment.

Requirement:

If critical Good Agriculture Practices (cGAP) e.g. AI dose/ ha, Pre harvest Interval (PHI) and number of applications is within a recommended range of conventional spray then; Data on phyto-toxicity on the approved crop for one season two different agro-climatic conditions, where the target crop is cultivated, to be generated as per protocol

New product registration with use of sprayers and Drones as spraying equipment or New label claim with the use of Drone alone as spraying equipment

Requirement:

Bio-efficacy data including phyto-toxicity on the desired/target crop-pest combination for two seasons in three different agro-climatic zones where the target crop is cultivated.

Residue data for two seasons three different agro-climatic zones where the target crop is cultivated.

Slide 12

Interim approval for application of already approved pesticide formulations through drones

477 nos. formulations of Insecticides/Fungicides/PGRs provisionally approved for use through drones for a period of 02 years.

applicants/registrants who wish to use already registered products for spray using drones shall intimate to the Secretariat of ClB&RC about the details of the products, dose and the crops for intended use along with action plan of data generation

For spray using drones beyond the two years interim period of approval, the registrants shall have to generate the requisite data during the interim period as per RC approved guidelines for application with drones and get it endorsed with the approval of the Registration Committee

The applicant, registrant, drone operator shall be solely liable to adhere to the requirements as prescribed in the "Standard Operating Procedure (SOP) for use of drone application with pesticides for crop protection” and to follow the guidelines and safety measures prescribed by the Central Insecticides Board and Registration Committee as envisaged under Rule 43 of the Insecticides Rules, '1971.

Slide 13

Roadmap to cater training needs and capacity building

NIPHM

CIPMCs

KVKs

SAUs

Department of Agriculture/ Horticulture

Drone Associations/ Drone operators

Pesticide Industry

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Drone-SOP-Final

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Annexure

Standard Operating Procedure (SOP) for use of Drone application with pesticides for crop protection in agricultural, forestry, non-cropped areas, etc.

Government of India Ministry of Agriculture and Farmers Welfare Department of Agriculture and Farmers Welfare Krishi Bhawan New Delhi

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prerequisites etc. for Drone based Pesticide application a. Pre-application b. During application c. Post application 5. Critical parameters to be considered 8-10 for Drone based pesticide application 5.1. Drone related 5.2. Pesticides/Insecticides 5.3. Environment Limitations 5.4. Pilot Training 5.5. Drift management-Critical Operational Parameters 5.6. Safe guarding the non-targets 6. Registration requirements

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Endorsement

This Standard Operating Procedure (SOP) for use of Drone application with pesticides for crop protection in agricultural, forestry, non-cropped areas, is prepared by the committee constituted vide O.M. No 13-15/2020-M&T (I&P), dated 31stof March, 2021 under the chairmanship of Plant Protection Adviser, Directorate of Plant Protection, Quarantine & Storage, Faridabad, for undertaking safe and effective control of Pest and diseases by Drone application with pesticides through aerial spraying. This SOP will render guidance to the stakeholders/ pilot/operators/ users/regulators while undertaking safe and effective control of Pest and diseases by Drone based Pesticide application.

(Dr Ravi Prakash) Plant Protection Adviser Directorate of Plant Protection, Quarantine & Storage, NH-IV, Faridabad-121001 India

LOCUST UNIT

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- Objective: Indian Agriculture has gone through rapid advancements and has benefited from research and adoption of new technologies by farmers. Technologies like drip irrigation, mechanized farming for planting, harvesting and grading are being successfully used for sustainable agriculture in India. In recent years, use of drone in agriculture has gained prominence and some states are actively engaged in checking the suitability of this new technology in Indian agriculture. Application of pesticides using drones has a great potential as we move towards commercialization and achieving precision in agricultural crops. Drones are going to be important for increasing efficiency of application of crop protection chemicals by reducing manpower requirement, reducing time of application, reducing volume of water, quantity of chemicals and saving drift to environment along with reducing exposure to human being to hazardous chemicals. In conventional agricultural practices, pesticides are sprayed either manually or with the help of tractor-mounted sprayers where high quantity of pesticides and water are used and where a sizable portion of spray goes waste in environment. However, drone-based spray requires less amount of water, as well as pesticides, due to better application and bioefficiency. To achieve the above stated objectives, Drones as a future technology for pesticide spraying, custom hiring and cooperative use will be encouraged and facilitated by Ministry of Agriculture and Farmers Welfare so that they are widely available and easily accessible to the farmers of the country. Drone as future technology for pesticide spraying are also expected to be linked with Agriculture insurance system for tackling any kind of damage and loss. The SOP for drone regulation for pesticide application therefore covers important aspects like statutory provisions, flying permissions, area distance restrictions, weight classification, overcrowded areas restriction, drone registration, safety insurance, piloting certification, operation plan, air flight zones, weather conditions, SOPs for pre, post and during operation, emergency handling plan etc. 203

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- Statutory Provisions: As per the provisions of the Insecticides Rules1971, Under the Insecticides Act, 1968 one of the functions of the board (Central Insecticides Board) constituted under section 4 of the Act, is to specify the uses of the classification of insecticides on the basis of their toxicity as well as their being suitable for aerial application [Rule 3 (b)]. Further, as per Insecticide Rules 1971, Chapter VIII Rule 43 on Aerial Spraying Operations, the aerial application of Insecticide shall be applicable for pesticide application through drones subject to the following provisions: a. marking of the area shall be the responsibility of the operators; b. the operators shall use only approved insecticides and their formulations at approved concentration and height; c. washing decontamination and first-aid facilities shall be provided by the operators; d. All aerial operations shall be notified to the public not less than twenty-four hours in advance through competent authorities (written intimation to be sent to the Executive Officer of the respective Gram Panchayat & Panchayat Samiti, as well as the concerned Agriculture Officer of the area, at least 24 hours in advance). e. Animals and persons not connected with the operations shall be prevented from entering such areas for a specific period; and f. The pilots shall undergo specialization training including clinical effects of the insecticides (details on Pilot Training are given at point no.5.4 of this SOP).
- The drone operations are being permitted by Ministry of Civil Aviation (M/o CA) and Director General of Civil Aviation (DGCA) through the conditional exemption route. New drone directorates have been established in DGCA recently to speed up the approval process. They have published a detailed DGCA

Requirements for Operation of Civil Remotely Piloted Aircraft System (RPAS) Guidance Manual with an objective to acquaint the public and the industry with the procedures being followed for processing all matter pertaining to issue of unique identification number, unmanned aircraft operator permit, and related activities. It will help understand the flow of various processes involved and understand the intricacies of the system. 204

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Further, Requirements for Operation of Civil Remotely Piloted Aircraft System (RPAS) mentions about the Civil Aviation Requirements (CAR) issued under the provisions of Rule 15A and Rule 133A of the Aircraft Rules, 1937 under the Aircraft Act, 1934 (22 of 1934)and lays down requirements for obtaining Unique Identification Number (UIN), Unmanned Aircraft Operator Permit (UAOP) and other operational requirements for civil Remotely Piloted Aircraft System (RPAS).These operations of drones are regulated by Unmanned Aircraft System (UAS) Rules, 2021, as published by Ministry of Civil Aviation vide G.S.R. 589(E) dated 25th August, 2021. Operators have the flexibility to utilize any RPAS/drone in case of agricultural pesticide spraying, irrespective of weight category or use case, provided the discharge of substance is cleared and mentioned in the Unmanned Aircraft Operator Permit(UAOP) issued by the DGCA.

- Details, precautions and prerequisites etc. for Drone based Pesticide application The following details, precautions, prerequisites etc. shall be adhered to before, during and postoperation: 4.1. Pre-application: i.

Confirm not to fly in the drone-forbidden area (airport or electronic station).No prior permission is required for operating an unmanned aircraft system in a green zone.

ii.

Ensure your Drone is Digital Sky Compliant with „No Permission – No Takeoff“ hardware and firmware;

iii.

Obtain Unique Identification Number (UIN) from DGCA for operating in controlled airspace and affix it on your drone.

iv.

Obtain Unmanned Aircraft Operator Permit (UAOP), if applicable from DGCA for commercial operations and keep it handy

v.

Ensure drone is in good condition (not damaged) and fit for flying safely.

vi.

Keep an eye on interference: Interference can be from mobile devices or blockage of signals, do watch out when flying your drone.

vii.

Fly in visual line of sight (VLOS): Always be within visual range of your drone.

viii.

Ensure the operators are trained on both drone operation and safe use pesticide.

ix.

No alcoholic drinks should be consumed within 8 hours preceding operation. 205

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x.

Calibrate drone spray system to ensure nozzle output and accurate application of labelled rates.

xi.

Check if drone is in good condition and that there is no leak in the spraying system.

xii.

Confirm a place for take-off, landing and tank mix operations.

xiii.

Check and mark proposed treated area, boundary, the obstacles (walls, trees) around the field for safe operation.

xiv.

Set up the least buffer zone (as specified by DGCA/ CIB&RC) between drone treatment and the non-target crop.

xv.

Confirm presence of water sources - Do not spray pesticides near water sources (less than 100 m from target area) to avoid polluting water sources.

xvi.

Check if the public has been notified/intimated at least twenty-four hours in advance through a written intimation to the competent authorities, that is the Executive Officer of the respective Gram Panchayat & Panchayat Samiti, as well asthe concerned Agriculture Officer of the area.

xvii.

Concerned territory in-charge/operators to ensure that animals and persons not connected with the operations shall be prevented from entering such areas for a specific period.

xviii.

Do log your flights and intimate concerned authorities (like DGCA, local police etc.)of any incidents/ accidents

xix.

Don‟t fly drone over groups of people, public events, or stadiums full of people without permission

xx.

Don‟t fly drone over government facilities/military bases or over/ near any no-drone zones.

xxi.

Don‟t fly drone over private property unless permission is given.

xxii.

Don't fly drone in controlled airspace near airports without filing flight plan or AAI/ADC permission (at least 24 hours before actual operation).

xxiii.

Don‟t drop or carry hazardous material

xxiv.

Don‟t fly drone from a moving vehicle, ship or aircraft.

xxv.

Don‟t fly the Drone in contraventions to theUnmanned Aircraft System Rules (UAS), 2021 rules as published by Ministry of Civil Aviation vide G.S.R. 589(E) dated 25thAugust, 2021and as amended from time to time.

4.2. During Application: 206

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i.

Read labels carefully to understand safety guidance.

ii.

Wear Personal Protect Equipment (PPE).

iii.

Do not eat, drink or smoke while spraying.

iv.

Confirm the flying route was reasonable to minimize turn around.

v.

Operation team shall always stay at the downwind end of the field and backlight direction.

vi.

Spray with pure water first to test operation for at least 5 minutes wherever feasible and required.

vii.

Ensure two-step dilutions to fully dissolve the pesticide.

viii.

Adopt proper pressure for optimized droplet spectrum (>100μm).

ix.

Check weather conditions for: a. Appropriate Wind speed, b. Appropriate Temperature, c. Appropriate Humidity

x.

Ensure appropriate flying height above target crop.

xi.

Ensure appropriate water volume.

xii.

Ensure appropriate flying speed.

xiii.

Avoid having to walk through crop which has been contaminated by drifting spray.

xiv.

Do not spray during active bee foraging period of the day. Avoid spray drift to flowering nectar crop.

xv.

When spraying pesticides that are toxic to non-target organisms such as fish, birds and silkworm, strictly abide by the product label requirements and take effective measures to avoid risks.

xvi.

Use anti-drift nozzle to decrease drift to human and environment.

4.3. Post Application: i.

Timely evacuation and transfer to fresh air.

ii.

Triple rinse of empty container is mandatory.

iii.

Ensure waste generated is kept to a minimum.

iv.

The disposal of waste must conform to the local laws.

v.

Never burn or bury hazardous waste. 207

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vi.

Never leave empty containers in the field. It should be disposed of

as per the

Insecticides Rule 1971. vii.

Set up warning signs in the spray area for reminding people.

viii.

Take a shower and put on clean clothes.

ix.

To prevent leakage of plant protection products in the process of transport and waiting to use.

x.

Securely store plant protection products away from unauthorized people, animals and food when transporting and storing PPP. Safely dispose all spills immediately.

xi.

Follow the maintenance schedule as prescribed by the Drone manufactures.

• Critical parameters to be considered for Drone based pesticide application: 5.1. Drone related: i.

ii.

iii. iv.

v. vi. vii.

Only Director General of Civil Aviation (DGCA) certified/approved drone shall be permitted to carry-out agriculture spray. The reliability of the drone is assured through DGCA certification process. The drone must have capability to handle variable payload (depleting tank). The nozzle system should be attached in a manner that the spray swath is continuous when sprayed from the minimum permitted height above the uniformly distributed crop (e.g. paddy/sugarcane). The drone must be fitted with accurate altitude sensor to ensure desired height above the crop is maintained throughout the spraying mission. The GPS accuracy of the drone and accuracy of the map shall be characterized and the same shall be utilized to define the safety/buffer margin while creating the geo-fencing around the field or obstacles. The drone spray system must support variable flow control to ensure uniform dispensing of the payload. The drone must have necessary fail-safes including Return to Home (RTH) on empty tank and auto mission restart from the point RTH was engaged. The drone spray system should be leak proof and dripping of Pesticides/Insecticides should be avoided during the application. (Check before flight)

5.2. Pesticides/Insecticides i. ii. iii.

Only Central Insecticides Board and Registration Committee (CIB&RC) approved Pesticides/Insecticides shall be used. The dose has to remain within the range approved by CIB&RC. The Pesticides/Insecticides (liquid/solid) compatibility with the drone spray system shall be established prior to the mission for the desired dilution. This is to ensure Pesticides/Insecticides solubility formulation stability and ability to spray with the type of

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nozzles provided in the drone. In case of mixing of more than one Pesticides / Insecticides, CIB&RC specified guidelines must be adhered to. The minimum dilution shall be decided based on the fulfilment of the above-mentioned requirements and ensuring satisfactory coverage of sprayed input both horizontally and vertically. Pesticides/Insecticides should be diluted only with clean water wherever applicable or with other suitable ingredient as has been approved by the CIB&RC.

iv.

v.

5.3.Environment Limitations The drone based spray should be undertaken and may be permitted under the conducive weather conditions to get the best results in terms of appropriate Wind speed, Temperature& Relative Humidity etc. 5.4. Pilot Training i. ii.

Only DGCA certified pilots shall be permitted to fly the agri drones. A training module as devised by NIPHM, Hyderabad encompassing pesticide/ insecticide handling, agri-mission specific operational protocols, and

relevant crop protection guidelines shall be made mandatory for pilots operating pesticide/ insecticide spray drones.

5.5.Drift Management -Critical Operational Parameters Majority of land holdings are small and there are possibilities of spray drift to the nearby crop fields while spraying with drones. To minimize the spray drift, apart from wind limitation, the following are important and to be suitably adopted: i. ii. iii. iv. v. vi.

Spray height above crop canopy Speed of the drone Suitable nozzles and Droplet size A buffer zone can be demarcated (geo fenced) Spray schedule should be at appropriate time gap either before rainfall or after rainfall. Others, as specified in guidelines issued by CIB&RC from time to time.

5.6.Safe guarding the non-targets The non-targets shall be safe guarded by adhering to the following operational protocols: i.

ii.

Buffer zone as per CIB&RC approved guidelines to cater to Pesticides/Insecticides drift, shall be maintained between the adjacent farms or different crops to avoid spray on non-targets. During the spray operation operator should always maintain the distance approved by CIB&RC from the drone and avoid windward direction as much as possible. 209

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iii. iv.

No human or animal movement shall be permitted within the farm during and immediately after the spray operations. Drone based pesticides spray operations should be conducted at a distance approved by CIB&RC from water bodies, residential areas, fodder crops, public utilities, dairy, poultry etc. and as per DGCA guidelines.

- Registration requirements of pesticides for drone application: The Registration requirements of pesticides for drone application and the modalities are dynamic in nature and will be considered based upon the safety, efficacy, statutory and legal requirements and published by the Central Insecticides Board and Registration committee (CIB&RC) from time to time. Drone users shall use only Central Insecticides Board and Registration Committee approved pesticides. For registration of insecticides/pesticides and for use with drone, the applicant shall apply before Secretariat of CIB&RC, in the manner, as prescribed by CIB&RC under the Insecticides Act, 1968. 7. Spray Monitoring Form& Data Submission: Spray monitoring data dully filled by the operator/ service provider shall be submitted through email(as mentioned in the guidelines issued by CIB&RC)/online portal created for the purpose, with-in seven days of application of pesticides through drone, in the form as prescribed in Annexure-I below. SPRAY MONITORING FORM Annexure-I 1 1-1 1-2 2 2-1 2-2 2-3 3 3-1 3-2 3-3 3-4 3-5 3-6 4 4-1 4-2

LOCATION of Trial Details Date Name of the location VEGETATION DATA Vegetation type (Crop, Grass, Bushes, Trees,) Height from ground/Crop Canopy (m) Crop names and pest/disease/weed infection/infestation/intensity (%) PESTICIDEDATA Trade name& Common name Concentration (g a.i./l or %) Formulation (EC, ULV, Dust) expiry date Is the insecticide mixed with water or solvent? If yes, what solvent and mixing ratio WEATHER CONDITIONS Start and end of control operations Date &time Temperature (°C)

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Relative humidity (%) Wind speed (m/s) Wind direction (degrees from N) Spray direction (degrees from N) SPRAY APPLICATION Sprayer type (Rotary, Airblast, ENS, Hydraulic, Other) Sprayer operator (Pilot, Driver, Hired, Other) Sprayer manufacturer Sprayer model Sprayer platform (Aerial, Vehicle, Handheld) Date of last calibration Atomizer height above ground (m) ROTARY SPRAYERS: speed setting (blade angle, pulley setting, no. batteries) Speed of atomizer (rpm) Flow rate setting (which nozzle or restrictor used) Flow rate/atomizer (l/min) Number of atomizers Track spacing (m) BARRIERS ONLY: width and spacing (m) Forward speed (km/h) AERIAL SPRAYING: support supplied Ground marking (GPS, Flag, Mirror, Smoke, Vehicle, None) CONTROL EFFICACY Effectiveness/mortality (%) Days after treatment/ time after treatment (hours) Yield of Crop/method of Effectiveness /mortality estimation (Quadrats, Target size, Visual, Cages, Other) SAFETY AND ENVIRONMENT Protective clothing: what did the operator wear? Was soap and water available? Who was informed of

spraying? (Farmers, Nomads, Villagers, Officials, Beekeeper, others, etc.) Effect on non-target organisms If yes, what type of effect? Details of anyone who felt unwell or if other problems were encountered Details about nearby water-bodies and water channels

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GP = ground party available RC = radio communication with aircraft TG = DGPS track guidance GP RC TG GP RC TG GP RC TG GP RC TG GP RC TG GP RC TG GFMSV GFMSV GFMSV GFMSV GFMSV GFMSV N N N N N N

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SPRAY MONITORING FORM Annexure-II 1 1-1 1-2 2 2-1 2-2 2-3 3 3-1 3-2 3-3 3-4 3-5 3-6 4 4-1 4-2 4-3 4-4 4-5 4-6 5 5-1 5-2 5-3 5-4 5-5 5-6 5-7 5-8

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5-17

LOCATION of Trial Details Date Name of the location VEGETATION DATA Vegetation type (Crop, Grass, Bushes, Trees,) Height from ground/Crop Canopy (m) Crop names and pest/disease/weed infection/infestation/intensity (%) PESTICIDEDATA Trade name& Common name Concentration (g a.i./l or %) Formulation (EC, ULV, Dust) expiry date Is the insecticide mixed with water or solvent? If yes, what solvent and mixing ratio WEATHER CONDITIONS Start and end of control operations Date &time Temperature (°C) Relative humidity (%) Wind speed (m/s) Wind direction (degrees from N) Spray direction (degrees from N) SPRAY APPLICATION Sprayer type (Rotary, Airblast, ENS, Hydraulic, Other) Sprayer operator (Pilot, Driver, Hired, Other) Sprayer manufacturer Sprayer model Sprayer platform (Aerial, Vehicle, Handheld) Date of last calibration Atomizer height above ground (m) ROTARY SPRAYERS: speed setting (blade angle, pulley setting, no. batteries) Speed of atomizer (rpm) Flow rate setting (which nozzle or restrictor used) Flow rate/atomizer (l/min) Number of atomizers Track spacing (m) BARRIERS ONLY: width and spacing (m) Forward speed (km/h) AERIAL SPRAYING: support supplied Ground marking (GPS, Flag, Mirror,

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GP = ground party available RC = radio communication with aircraft TG = DGPS track guidance GP RC TG GP RC TG GP RC TG GP RC TG GP RC TG GP RC TG GFMSV GFMSV GFMSV GFMSV GFMSV GFMSV

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Smoke, Vehicle, None) CONTROL EFFICACY Effectiveness/mortality (%) Days after treatment/ time after treatment (hours) Yield of Crop/method of Effectiveness /mortality estimation (Quadrats, Target size, Visual, Cages, Other) SAFETY AND ENVIRONMENT Protective clothing: what did the operator wear? Was soap and water available? Who was informed of spraying? (Farmers, Nomads, Villagers, Officials, Beekeeper, others, etc.) Effect on non-target organisms If yes, what type of effect? Details of anyone who felt unwell or if other problems were encountered Details about nearby water-bodies and water channels

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Drones (1)

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Actuation Drones in Agriculture: Advancing Precision Pest Management through Biocontrol and Modern Techniques Raja Reddy Gundreddy a, Gunturi Alekhya b, Vidya Madhuri E a, Jayanth, BV a, Sibananda Darjee c, Shashikala, M a, B. Thirupam Reddy d and Nikitha Reddy Gaddam e* a Biological Control Laboratory, Division of Entomology, ICAR-Indian Agricultural Research Institute,

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Review Article

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ABSTRACT As global food demand surges, agricultural technology is essential for addressing challenges like environmental degradation, pollution, and water scarcity. Drones, or Unmanned Aerial Vehicles (UAVs), present a promising solution for precision agriculture by providing real-time, accurate data that enhances decision-making in crop management. In pest control, drones offer targeted delivery of natural enemies and biopesticides, improving efficiency and reducing reliance on chemical pesticides. This precision can lead to increased crop yields, reduced environmental impact, and improved livelihoods for farmers by lowering operational costs and optimizing resource use. Despite their potential, adopting drone technology in agriculture faces regulatory challenges, such as the need for certifications, flight restrictions, and operational guidelines. Addressing these regulatory hurdles is crucial for broader implementation. Moreover, collaboration among stakeholders—including researchers, policymakers, agricultural extension workers, and industry players—is vital for advancing drone-assisted pest management and ensuring its practical adoption in diverse farming environments. As we navigate these challenges, actuation drones hold immense promise for transforming pest management practices globally, contributing to sustainable agriculture and enhanced food

security. Further research, development, and stakeholder engagement are necessary to fully realize the potential of drones in integrated pest management (IPM) systems.

Keywords: Unmanned aerial vehicles; actuation drones; natural enemies; biopesticides; sterile insect technique; mating disruption.

- INTRODUCTION As the global population grows, technology in agriculture is becoming increasingly crucial for ensuring food security amidst challenges like environmental degradation, pollution, and water scarcity [1]. Drones, or UAVs (Unmanned Aerial Vehicles), offer a promising solution by providing precise and efficient agricultural management [2]. Equipped with advanced sensors, drones can capture real-time, detailed data that goes beyond human visual capabilities, allowing for more accurate and reliable information [3]. Drones are used in many fields, including military, cinematography, and disaster management. In agriculture, they are emerging as a key technology for precision farming and sustainable agriculture. They help address issues like labor shortages and health risks from chemicals [4]. By utilizing various sensors, drones contribute to precision pest management in two main ways: detecting pest hotspots and delivering solutions [5]. Sensing drones identify areas with high pest populations using remote sensing technologies. While aircraft have long been used for pesticide application, they often result in significant pesticide drift and environmental harm [6,7]. Drones offer a more precise alternative, potentially reducing the area and quantity of

pesticide use [8]. Moreover, drones can enhance biological control by efficiently distributing natural enemies in specific locations, increasing their efficacy and reducing costs [9]. In contrast, actuation drones are designed to release natural enemies, such as predatory insects or parasitoids, exactly where they are needed. This targeted approach improves the effectiveness of biological control and reduces reliance on chemical pesticides [10]. Combining these drones in a closed-loop system can provide a cost-effective and environmentally friendly pest management solution. Biological control involves using one organism to manage another, with many commercially available options like parasitoids and entomopathogenic nematodes [10]. Drones could improve the application of these agents, which are often dispersed manually or using other equipment [11]. While the use of drones for distributing natural enemies is still developing, they promise to make biological control more accessible and effective compared to traditional methods [12,13]. This review will delve into the capabilities of actuation drones for the precision distribution of natural enemies, explore their role in modern pest management, and discuss the challenges and opportunities for their broader adoption in agriculture.

- ACTUATION DRONES FOR PRECISION RELEASES OF NATURAL ENEMIES Drones have emerged as versatile tools in various sectors, including agriculture, where they hold promise for augmentative biological control [14]. Augmentative biological control relies on the large-scale release of natural enemies for immediate pest management [10]. These natural enemies, such as predators, parasitoids, and pathogens, help in managing pest populations without the need for chemical pesticides [15]. The application of drones in this field could revolutionize biological control methods by increasing the efficiency of distributing natural enemies precisely where they are needed [16]. The ability of drones to distribute natural enemies across large areas offers significant advantages [16]. Unlike manual distribution methods, drones can cover extensive fields quickly, reducing the time and labor involved [17]. Furthermore, targeted delivery of biological control agents may enhance their efficacy by placing them directly in pest hotspots. This precision could reduce overall application costs and improve the success rates of biological control programs [18]. Certain natural enemies, such as insect-killing fungi and nematodes, can already be applied using conventional spray equipment [5,11]. As drones are increasingly used for pesticide application [19], the integration of these biocontrol agents with drone technology could follow a similar path. The automation and programmability of drones allow for tailored applications based on specific environmental conditions, further optimizing the release process [20]. However, not all natural enemies can be applied as easily as fungi or nematodes. The release of larger predators or parasitoids, for instance, is often more complex, time-consuming, and costly. Various mechanical distribution systems have been developed to facilitate the dispersal of predators, but their application remains a challenge [21]. Despite this, the versatility of drones could still provide a solution. By adapting drones with appropriate release mechanisms, they could be used to deploy a wider

range of natural enemies in diverse environments [14]. Historically, the idea of using aircraft to distribute biological control agents was explored in the

1980s [22,23]. While these early efforts demonstrated potential, the high cost and limited technology available at the time restricted widespread adoption (Table - 1). Modern drones, on the other hand, are smaller, more affordable, and capable of accessing areas that are difficult for larger aircraft to reach [24]. This opens up a myriad of possibilities for enhancing biological control efforts on both small and large scales. Drones represent a promising tool for augmentative biological control, offering precision, efficiency, and reduced costs. By enabling the targeted release of natural enemies, drones could increase the adoption of biological control methods, potentially reducing reliance on chemical pesticides [25]. As technology continues to advance, drones may play a crucial role in sustainable pest management practices, bridging the gap between traditional methods and modern innovations. However, further research and development are needed to overcome challenges related to the deployment of certain natural enemies and to optimize droneassisted biological control systems [26].

- ACTUATION DRONES PRECISION RELEASES BIOPESTICIDES

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Actuation drones are used in agriculture to apply biopesticides directly and precisely to targeted areas within fields. These drones use advanced technology to control the release of biopesticides based on real-time data, making them especially useful for managing pest outbreaks in large farms where traditional methods may be less effective [19]. Biopesticides include various types, such as microbial agents (bacteria, fungi, viruses), plant extracts, and biochemical substances. Drones can be equipped to handle different forms of biopesticides, including liquid sprays and dry powders, ensuring they are applied effectively [5,11]. One major advantage of using drones for biopesticide application is the reduction of pesticide drift, which is the spread of pesticides beyond the intended target. Traditional methods can cause harm to beneficial insects, wildlife, and ecosystems due to drift, but drones allow for more precise application, reducing the amount of biopesticide needed and minimizing harm to nontarget organisms [27,28,14].

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Gundreddy et al.; J. Exp. Agric. Int., vol. 46, no. 9, pp. 825-835, 2024; Article no.JEAI.123388

Table 1. Actuation Drones for Precision Releases of Natural Enemies Sl no. 1.

Natural Enemies Egg parasitoid

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Egg parasitoid

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Mile-a-minute weevil Lacewings

5.

defoliating moth

6.

Egg parasitoid

7.

ectoparasitoid

Scientific name

Family and Order

Insect pest

Scientific name

Trichogramma ostriniae Trichogramma minutum Rhinoncomimus latipes Korotyaev Chrysoperla rufilabris (Burmeister) Neomusotima conspurcatalis Warren Trichogramma ostriniae Tamarixia radiata Waterston

Hymenoptera: Trichogrammatidae Hymenoptera: Trichogrammatidae Coleoptera: Curculionidae Neuroptera: Chrysopidae Lepidoptera: Crambidae Hymenoptera: Trichogrammatidae Hymenoptera: Eulophidae

European corn Borer Eastern spruce budworm, Mile-a-minute weed Lettuce aphid,

Ostrinia nubilalis Hübner Choristoneura fumiferana Clemens Persicaria perfoliata (L.) H. Gross Nasonovia ribisnigri (Mosley) Lygodium microphyllum Ostrinia furnacalis (Guenée) Diaphorina citri Kuwayama

Old World climbing fern, Corn Borer Asian citrus psyllid

Family and Order Lepidoptera: Crambidae) Lepidoptera: Tortricidae Caryophyllales: Polygonaceae Hemiptera: Aphididae Lygodiaceae

References

Lepidoptera: Crambidae Hemiptera: Psyllidae

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Table 2. Reducing Pest Populations:Sterile Insect Technique and Mating Disruption 1.

- 3. 4. 5.

Common Name Sterile Mexican fruit fly

Scientific name Anastrepha ludens(Loew)

Family and Order (Diptera: Tephritidae)

Sterile Codling Moth Cranberry fruitworm Sterile Codling Moth sterile male

Cydia Pomonella (Linnaeus) Acrobasis Vaccinii (Riley) Cydia Pomonella (Linnaeus) Aedes aegypti

Male Mosquitoes

Aedes aegypti

(Lepidoptera: Tortricidae) Lepidoptera: Pyralidae) (Lepidoptera: Tortricidae) (Diptera: Culicidae) (Diptera: Culicidae)

Mechanism Designed a conveyor belt mechanism underneath a straight walled insect compartment to meter and expel insects Release device Comparing Deliveries of Sterile Codling Moth by Two Types of Unmanned Aerial Systems and from the Ground Mating disruption extruder system that effectively delivered one gram droplets of mating disruption over cranberry beds Combined Effects of Mating Disruption, Insecticides,

References [35]

Release of Sterile Mosquitoes with Drones in Urban and Rural Environments The Effect of Storage Conditions on Survival of Male Mosquitoes During Transport

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Table 3. Actuation Drones for Precision Releases of Biopesticides Biopesticide Metarhizium rileyi Bacillus thuringiensis var. israelensis Bacillus thuringiensis liquid formulation (conidia+diesel) of Metarhzium acridum (Farlow) Kepler, Rehner and Humber

Insect pest Fall armyworm and soybean looper Aedes vigilax (Skuse) Bagworm, Metisa plana WALKER Desert locust, Schistocerca gregaria (Forsk.)

References [40] [41] [42] [43]

Drones also improve labor and operational efficiency by automating the application process, reducing the need for manual labor, and lowering costs. They can access hard-to-reach areas within fields, ensuring complete coverage for pest control [26,12,13].

methods offer sustainable alternatives to chemical pesticides and can be seamlessly integrated into broader Integrated Pest Management (IPM) strategies.

However, there are challenges in adopting drone technology for biopesticide application, including the high cost of drones, the need for specialized training, and regulatory concerns. Despite these challenges, advances in drone technology and decreasing costs are making this method more accessible to farmers [44].

The Sterile Insect Technique (SIT) involves mass-rearing and sterilizing insects, typically through irradiation, and releasing them into the wild. When these sterile insects mate with wild counterparts, the resulting offspring are either sterile or non-existent, leading to a gradual reduction in pest populations [45]. SIT has been widely recognized as a valuable tool in IPM due to its precision, minimal environmental impact, and compatibility with other management methods [46].

Recent developments in drone technology have opened new possibilities for more efficient pest management. While some progress has been made in using drones to apply biological control agents, there is still limited information on drone application parameters and the effectiveness of these agents when delivered by drones. Some studies have shown success with specific organisms, like the bacterium Bacillus thuringiensis, but more research is needed, especially with entomopathogenic fungi (Table 3). For example, a study on spraying the fungus Metarhizium acridum by drone showed that factors like flight configuration, weather, and vegetation type significantly affected the deposition of the fungus. Despite some drift during dusting, spraying biopesticides with drones was found to be more uniform and effective [41,42,43].

- REDUCING PEST POPULATIONS WITH DRONES: STERILE INSECT TECHNIQUE AND MATING DISRUPTION
  Drones are emerging as innovative tools for pest management, particularly in enhancing techniques like the Sterile Insect Technique (SIT) and mating disruption [37]. These environmentally friendly, species-specific

4.1 Sterile Insect Technique (SIT)

Traditionally, sterile insects have been released through ground-based methods such as allterrain vehicles (ATVs) or by manned aircraft [47]. However, these methods can be expensive, labor-intensive, and less precise, limiting the wider adoption of SIT. Drones offer a promising alternative. By enabling aerial releases at targeted locations, drones can increase the effectiveness of sterile insect dispersal while reducing the costs associated with ground releases.The cost-effectiveness and precision of drones may help expand the use of SIT to new regions and crops, making it more accessible to growers [48].

4.2 Mating Disruption In addition to SIT, drones can play a pivotal role in implementing mating disruption techniques. Mating disruption relies on the strategic release of pheromones that interfere with pests' ability to find mates, effectively reducing their reproduction rates [49]. One common product used in mating disruption is SPLAT (Specialized Pheromone & Lure Application Technology), an inert matrix that can be infused with pheromones or pesticides and applied as dollops [50].

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Drones provide an efficient and precise method for deploying mating disruptors across large commercial fields [51]. Their ability to navigate difficult terrains and apply disruptors at specific locations ensures more effective coverage compared to manual application methods. Additionally, drones can be used for attract-andkill strategies, which combine pheromones with a killing agent, drawing pests in and eliminating them [52]. The combination of these methods has proven to be effective in managing a variety of pests across different cropping systems. The integration of drones into pest management strategies like SIT and mating disruption represents a significant advancement in sustainable agriculture [53]. Drones offer precision, cost efficiency, and the ability to cover large areas quickly, making them ideal for the release of sterile insects and the deployment of pheromone-based disruptors [54]. As these technologies continue to evolve, they hold the potential to reduce the reliance on chemical pesticides and increase the adoption of environmentally friendly

pest control methods [14]. By bridging the gap between traditional techniques and modern innovations, drones are set to play an increasingly important role in IPM and the future of pest management (Table - 2).

4.3 Potential and Limits of UAS for Trichogramma Releases ✓✓

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The Trichocards offer some protection against both abiotic conditions and predation While Trichocards can be installed under any weather conditions, UAS have some constraints regarding mainly winds and their flight duration is limited by the battery autonomy. The regulations surrounding the use of UAS can also have an impact on its use for biological control applications. A tight timing of the UAS bulk release right before parasitoid emergence could offer a good solution, although the costs of parasitoids emerging too early would be even more detrimental. Releasing capsules containing the biocontrol agents could also offer parasitoids a protection. Bulk releases allow the dispersion of parasitoids during release while capsules act more like Trichocards where the parasitoid dispersal comes from punctual points instead of spreading in the field/forest.

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Trichocards and capsules also require more work, which of course adds to costs. However, preparing capsules is faster than preparing Trichocards, given that the proper installations are available. Of course, UAS also carry operation costs, that may vary based on whether they are done by producers, forest managers, or by service providers. UAS also brings the benefit of being potentially coupled with imagery that could detect the presence of the pest, and more precisely release biocontrol agents only on the specific part of the field/forests that need them, avoiding non-host or healthy plants.

- ACTUATION DRONES AGRICULTURE

IN

INDIAN

In the rapidly evolving landscape of Indian agriculture, the adoption of advanced technologies is becoming increasingly critical to meet the challenges posed by growing food demand, climate change, and resource constraints [55]. Actuation drones, a key innovation in precision pest management, offer transformative potential by enabling targeted and efficient application of biocontrol agents. These drones, equipped with sophisticated sensors and release mechanisms, can precisely distribute natural enemies, such as predators and parasitoids, directly to pest hotspots, reducing the need for chemical pesticides and enhancing the sustainability of agricultural practices [24]. In India, where smallholder farmers often struggle with the high costs and environmental impacts of conventional pest control methods, actuation drones present an opportunity to improve crop yields and reduce losses [56]. By facilitating the application of biological control agents, such as Trichogramma, drones can help manage pests like the fall armyworm and cotton bollworm, which pose significant threats to major crops. Additionally, drones can be utilized for the precision release of biopesticides, further minimizing environmental harm and protecting beneficial organisms [29]. However, the widespread adoption of actuation drones in Indian agriculture faces several challenges, including regulatory hurdles, high upfront costs, and the need for specialized training. Regulatory frameworks governing drone usage in agriculture are still evolving, with requirements for certifications, operational approvals, and adherence to safety standards.

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Overcoming these challenges will require concerted efforts from policymakers, industry leaders, and agricultural extension services [57].

5.2 Disadvantages 1. High Initial Costs: The acquisition of drones and related equipment can be expensive, posing a barrier for small-scale farmers. 2. Specialized Training: Operating drones for pest management requires specialized training, which may not be readily available to all users. 3. Regulatory Challenges: Compliance with regulations governing drone use in agriculture varies by region and can be complex,

potentially limiting widespread adoption. 4. Technical Limitations: Factors such as weather conditions, flight endurance, and payload capacity may restrict the effectiveness of drone applications in certain environments. 5. Limited Research: While some progress has been made, more research is needed on drone application parameters, particularly for certain biological agents like entomopathogenic fungi. 6. Maintenance and Upkeep: Regular maintenance and technical support are required to ensure drones operate effectively, adding to operational costs [59,60].

The successful integration of drone technology in Indian agriculture will also depend on collaboration among key stakeholders. Government support, in the form of subsidies or incentives, can make drone technology more accessible to smallholder farmers. Additionally, partnerships between research institutions, technology providers, and farmer cooperatives can facilitate the transfer of knowledge and skills needed to optimize drone usage for pest management [58]. As India continues to modernize its agricultural sector, actuation drones have the potential to play a pivotal role in enhancing productivity, sustainability, and food security. By reducing the reliance on chemical pesticides and promoting precision biocontrol, these drones offer a forward-looking solution to the challenges of pest management in Indian agriculture. With the right policies, investments, and stakeholder engagement, actuation drones can become a cornerstone of modern pest management practices across the country [58].

5.1 Advantages 1. Precision Application: Drones enable precise distribution of biological control agents, biopesticides, and pheromones, reducing wastage and ensuring targeted application in pest hotspots. 2. Cost and Time Efficiency: Drone-assisted releases reduce labor costs and time spent on manual distribution methods, especially in large or difficult-to-access fields. 3. Environmental Benefits: By promoting the use of biological control and reducing reliance on chemical pesticides, drones contribute to environmentally sustainable pest management. 4. Coverage of Large Areas: Drones can cover extensive fields quickly and efficiently, making them suitable for largescale agricultural operations. 5. Adaptability: Drones can be programmed for specific tasks and adjusted based on real-time data, making them versatile for different pest management scenarios. 6. Reduction in Pesticide Drift: The precision of drones reduces the risk of pesticide drift, minimizing harm to non-target organisms and ecosystems.

- CONCLUSION The integration of drones into pest management practices represents a significant advancement in sustainable agriculture. Drones provide precision, cost efficiency, and environmental benefits, making them ideal for tasks such as the release of natural enemies, biopesticide application, and mating disruption. By addressing the challenges associated with drone technology, including costs, training, and regulations, the agricultural sector can unlock the full potential of drones for pest management. As research continues to evolve, drones are likely to play an increasingly important role in reducing the reliance on chemical pesticides and enhancing the effectiveness of IPM strategies.
- FUTURE PROSPECTS

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- Advancements in Drone Technology: Future developments in drone technology, including increased payload capacity, longer flight times, and enhanced automation, will improve the efficiency of drone-assisted pest management systems.

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- Cost Reduction: As drone technology becomes more widespread, the cost of acquiring and operating drones is expected to decrease, making them more accessible to a broader range of farmers. 3. Integration with AI and Data Analytics: The combination of drones with artificial intelligence (AI) and data analytics could enable real-time monitoring and decisionmaking, further optimizing pest management practices. 4. Expansion of Biocontrol Research: Continued research on the application of various biocontrol agents using drones will provide insights into best practices and improve the effectiveness of these agents. 5. Sustainability and Ecosystem Impact: Drones will contribute to more sustainable agricultural practices by minimizing the environmental impact of pest management and promoting biodiversity conservation. 6. Policy and Regulatory Frameworks: As the use of drones in agriculture expands, more streamlined and supportive regulatory frameworks will be necessary to facilitate their adoption while ensuring safety and environmental protection.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

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Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript. 11.

COMPETING INTERESTS Authors have interests exist.

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no competing 12.

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Actuation Drones in Agriculture: Advancing Precision Pest Management through Biocontrol and Modern Techniques Raja Reddy Gundreddy a, Gunturi Alekhya b, Vidya Madhuri E a, Jayanth, BV a, Sibananda Darjee c, Shashikala, M a, B. Thirupam Reddy d and Nikitha Reddy Gaddam e* a Biological Control Laboratory, Division of Entomology, ICAR-Indian Agricultural Research Institute,

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Review Article

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ABSTRACT As global food demand surges, agricultural technology is essential for addressing challenges like environmental degradation, pollution, and water scarcity. Drones, or Unmanned Aerial Vehicles (UAVs), present a promising solution for precision agriculture by providing real-time, accurate data that enhances decision-making in crop management. In pest control, drones offer targeted delivery of natural enemies and biopesticides, improving efficiency and reducing reliance on chemical pesticides. This precision can lead to

increased crop yields, reduced environmental impact, and improved livelihoods for farmers by lowering operational costs and optimizing resource use. Despite their potential, adopting drone technology in agriculture faces regulatory challenges, such as the need for certifications, flight restrictions, and operational guidelines. Addressing these regulatory hurdles is crucial for broader implementation. Moreover, collaboration among stakeholders—including researchers, policymakers, agricultural extension workers, and industry players—is vital for advancing drone-assisted pest management and ensuring its practical adoption in diverse farming environments. As we navigate these challenges, actuation drones hold immense promise for transforming pest management practices globally, contributing to sustainable agriculture and enhanced food security. Further research, development, and stakeholder engagement are necessary to fully realize the potential of drones in integrated pest management (IPM) systems.

Keywords: Unmanned aerial vehicles; actuation drones; natural enemies; biopesticides; sterile insect technique; mating disruption.

- INTRODUCTION As the global population grows, technology in agriculture is becoming increasingly crucial for ensuring food security amidst challenges like environmental degradation, pollution, and water scarcity [1]. Drones, or UAVs (Unmanned Aerial Vehicles), offer a promising solution by providing precise and efficient agricultural management [2]. Equipped with advanced sensors, drones can capture real-time, detailed data that goes beyond human visual capabilities, allowing for more accurate and reliable information [3]. Drones are used in many fields, including military, cinematography, and disaster management. In agriculture, they are emerging as a key technology for precision farming and sustainable agriculture. They help address issues like labor shortages and health risks from chemicals [4]. By utilizing various sensors, drones contribute to precision pest management in two main ways: detecting pest hotspots and delivering solutions [5]. Sensing drones identify areas with high pest populations using remote sensing technologies. While aircraft have long been used for pesticide application, they often result in significant pesticide drift and environmental harm [6,7]. Drones offer a more precise alternative, potentially reducing the area and quantity of

pesticide use [8]. Moreover, drones can enhance biological control by efficiently distributing natural enemies in specific locations, increasing their efficacy and reducing costs [9]. In contrast, actuation drones are designed to release natural enemies, such as predatory insects or parasitoids, exactly where they are needed. This targeted approach improves the effectiveness of biological control and reduces reliance on chemical pesticides [10]. Combining these drones in a closed-loop system can provide a cost-effective and environmentally friendly pest management solution. Biological control involves using one organism to manage another, with many commercially available options like parasitoids and entomopathogenic nematodes [10]. Drones could improve the application of these agents, which are often dispersed manually or using other equipment [11]. While the use of drones for distributing natural enemies is still developing, they promise to make biological control more accessible and effective compared to traditional methods [12,13]. This review will delve into the capabilities of actuation drones for the precision distribution of natural enemies, explore their role in modern pest management, and discuss the challenges and opportunities for their broader adoption in agriculture.

- ACTUATION DRONES FOR PRECISION RELEASES OF NATURAL ENEMIES Drones have emerged as versatile tools in various sectors, including agriculture, where they hold promise for augmentative biological control [14]. Augmentative biological control relies on the large-scale release of natural enemies for immediate pest management [10]. These natural enemies, such as predators, parasitoids, and pathogens, help in managing pest populations without the need for chemical pesticides [15]. The application of drones in this field could revolutionize biological control methods by increasing the efficiency of distributing natural enemies precisely where they are needed [16]. The ability of drones to distribute natural enemies across large areas offers significant advantages [16]. Unlike manual distribution methods, drones can cover extensive fields quickly, reducing the time and labor involved [17]. Furthermore, targeted delivery of biological control agents may enhance their efficacy by placing them directly in pest hotspots. This precision could reduce overall application costs and improve the success rates of biological control programs [18]. Certain natural enemies, such as insect-killing fungi and nematodes, can already be applied using conventional spray equipment [5,11]. As drones are increasingly used for pesticide application [19], the integration of these

biocontrol agents with drone technology could follow a similar path. The automation and programmability of drones allow for tailored applications based on specific environmental conditions, further optimizing the release process [20]. However, not all natural enemies can be applied as easily as fungi or nematodes. The release of larger predators or parasitoids, for instance, is often more complex, time-consuming, and costly. Various mechanical distribution systems have been developed to facilitate the dispersal of predators, but their application remains a challenge [21]. Despite this, the versatility of drones could still provide a solution. By adapting drones with appropriate release mechanisms, they could be used to deploy a wider range of natural enemies in diverse environments [14]. Historically, the idea of using aircraft to distribute biological control agents was explored in the

1980s [22,23]. While these early efforts demonstrated potential, the high cost and limited technology available at the time restricted widespread adoption (Table - 1). Modern drones, on the other hand, are smaller, more affordable, and capable of accessing areas that are difficult for larger aircraft to reach [24]. This opens up a myriad of possibilities for enhancing biological control efforts on both small and large scales. Drones represent a promising tool for augmentative biological control, offering precision, efficiency, and reduced costs. By enabling the targeted release of natural enemies, drones could increase the adoption of biological control methods, potentially reducing reliance on chemical pesticides [25]. As technology continues to advance, drones may play a crucial role in sustainable pest management practices, bridging the gap between traditional methods and modern innovations. However, further research and development are needed to overcome challenges related to the deployment of certain natural enemies and to optimize droneassisted biological control systems [26].

- ACTUATION DRONES PRECISION RELEASES BIOPESTICIDES

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Actuation drones are used in agriculture to apply biopesticides directly and precisely to targeted areas within fields. These drones use advanced technology to control the release of biopesticides based on real-time data, making them especially useful for managing pest outbreaks in large farms where traditional methods may be less effective [19]. Biopesticides include various types, such as microbial agents (bacteria, fungi, viruses), plant extracts, and biochemical substances. Drones can be equipped to handle different forms of biopesticides, including liquid sprays and dry powders, ensuring they are applied effectively [5,11]. One major advantage of using drones for biopesticide application is the reduction of pesticide drift, which is the spread of pesticides beyond the intended target. Traditional methods can cause harm to beneficial insects, wildlife, and ecosystems due to drift, but drones allow for more precise application, reducing the amount of biopesticide needed and minimizing harm to nontarget organisms [27,28,14].

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Table 1. Actuation Drones for Precision Releases of Natural Enemies Sl no. 1.

Natural Enemies Egg parasitoid

2.

Egg parasitoid

- 4.

Mile-a-minute weevil Lacewings

5.

defoliating moth

6.

Egg parasitoid

7.

ectoparasitoid

Scientific name

Family and Order

Insect pest

Scientific name

Trichogramma ostriniae Trichogramma minutum Rhinoncomimus latipes Korotyaev Chrysoperla rufilabris (Burmeister) Neomusotima conspurcatalis Warren Trichogramma ostriniae Tamarixia radiata Waterston

Hymenoptera: Trichogrammatidae Hymenoptera: Trichogrammatidae Coleoptera: Curculionidae Neuroptera: Chrysopidae Lepidoptera: Crambidae Hymenoptera: Trichogrammatidae Hymenoptera: Eulophidae

European corn Borer Eastern spruce budworm, Mile-a-minute weed Lettuce aphid,

Ostrinia nubilalis Hübner Choristoneura fumiferana Clemens Persicaria perfoliata (L.) H. Gross Nasonovia ribisnigri (Mosley) Lygodium microphyllum Ostrinia furnacalis (Guenée) Diaphorina citri Kuwayama

Old World climbing fern, Corn Borer Asian citrus psyllid

Family and Order Lepidoptera: Crambidae) Lepidoptera: Tortricidae Caryophyllales: Polygonaceae Hemiptera: Aphididae Lygodiaceae

References

Lepidoptera: Crambidae Hemiptera: Psyllidae

[33]

[29] [29] [30] [31] [32]

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Table 2. Reducing Pest Populations:Sterile Insect Technique and Mating Disruption 1.

- 3. 4. 5.

Common Name Sterile Mexican fruit fly

Scientific name Anastrepha ludens(Loew)

Family and Order (Diptera: Tephritidae)

Sterile Codling Moth Cranberry fruitworm Sterile Codling Moth sterile male

Cydia Pomonella (Linnaeus) Acrobasis Vaccinii (Riley) Cydia Pomonella (Linnaeus) Aedes aegypti

Male Mosquitoes

Aedes aegypti

(Lepidoptera: Tortricidae) Lepidoptera: Pyralidae) (Lepidoptera: Tortricidae) (Diptera: Culicidae) (Diptera: Culicidae)

Mechanism Designed a conveyor belt mechanism underneath a straight walled insect compartment to meter and expel insects Release device Comparing Deliveries of Sterile Codling Moth by Two Types of Unmanned Aerial Systems and from the Ground Mating disruption extruder system that effectively delivered one gram droplets of mating disruption over cranberry beds Combined Effects of Mating Disruption, Insecticides,

References [35]

Release of Sterile Mosquitoes with Drones in Urban and Rural Environments The Effect of Storage Conditions on Survival of Male Mosquitoes During Transport

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[26] [36] [37]

[39]

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Table 3. Actuation Drones for Precision Releases of Biopesticides Biopesticide Metarhizium rileyi Bacillus thuringiensis var. israelensis Bacillus thuringiensis liquid formulation (conidia+diesel) of Metarhzium acridum (Farlow) Kepler, Rehner and Humber

Insect pest Fall armyworm and soybean looper Aedes vigilax (Skuse) Bagworm, Metisa plana WALKER Desert locust, Schistocerca gregaria (Forsk.)

References [40] [41] [42] [43]

Drones also improve labor and operational efficiency by automating the application process, reducing the need for manual labor, and lowering costs. They can access hard-to-reach areas within fields, ensuring complete coverage for pest control [26,12,13].

methods offer sustainable alternatives to chemical pesticides and can be seamlessly integrated into broader Integrated Pest Management (IPM) strategies.

However, there are challenges in adopting drone technology for biopesticide application, including the high cost of drones, the need for specialized training, and regulatory concerns. Despite these challenges, advances in drone technology and decreasing costs are making this method more accessible to farmers [44].

The Sterile Insect Technique (SIT) involves mass-rearing and sterilizing insects, typically through irradiation, and releasing them into the wild. When these sterile insects mate with wild counterparts, the resulting offspring are either sterile or non-existent, leading to a gradual reduction in pest populations [45]. SIT has been widely recognized as a valuable tool in IPM due to its precision, minimal environmental impact, and compatibility with other management methods [46].

Recent developments in drone technology have opened new possibilities for more efficient pest management. While some progress has been made in using drones to apply biological control agents, there is still limited information on drone application parameters and the effectiveness of these agents when delivered by drones. Some studies have shown success with specific organisms, like the bacterium Bacillus thuringiensis, but more research is needed, especially with entomopathogenic fungi (Table 3). For example, a study on spraying the fungus Metarhizium acridum by drone showed that factors like flight configuration, weather, and vegetation type significantly affected the deposition of the fungus. Despite some drift during dusting, spraying biopesticides with drones was found to be more uniform and effective [41,42,43].

- REDUCING PEST POPULATIONS WITH DRONES: STERILE INSECT TECHNIQUE AND MATING DISRUPTION Drones are emerging as innovative tools for pest management, particularly in enhancing techniques like the Sterile Insect Technique (SIT) and mating disruption [37]. These environmentally friendly, species-specific

4.1 Sterile Insect Technique (SIT)

Traditionally, sterile insects have been released through ground-based methods such as allterrain vehicles (ATVs) or by manned aircraft [47]. However, these methods can be expensive, labor-intensive, and less precise, limiting the wider adoption of SIT. Drones offer a promising alternative. By enabling aerial releases at targeted locations, drones can increase the effectiveness of sterile insect dispersal while reducing the costs associated with ground releases.The cost-effectiveness and precision of drones may help expand the use of SIT to new regions and crops, making it more accessible to growers [48].

4.2 Mating Disruption In addition to SIT, drones can play a pivotal role in implementing mating disruption techniques. Mating disruption relies on the strategic release of pheromones that interfere with pests' ability to find mates, effectively reducing their reproduction rates [49]. One common product used in mating disruption is SPLAT (Specialized Pheromone & Lure Application Technology), an inert matrix that can be infused with pheromones or pesticides and applied as dollops [50].

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Drones provide an efficient and precise method for deploying mating disruptors across large commercial fields [51]. Their ability to navigate difficult terrains and apply disruptors at specific locations ensures more effective coverage compared to manual application methods. Additionally, drones can be used for attract-andkill

strategies, which combine pheromones with a killing agent, drawing pests in and eliminating them [52]. The combination of these methods has proven to be effective in managing a variety of pests across different cropping systems. The integration of drones into pest management strategies like SIT and mating disruption represents a significant advancement in sustainable agriculture [53]. Drones offer precision, cost efficiency, and the ability to cover large areas quickly, making them ideal for the release of sterile insects and the deployment of pheromone-based disruptors [54]. As these technologies continue to evolve, they hold the potential to reduce the reliance on chemical pesticides and increase the adoption of environmentally friendly pest control methods [14]. By bridging the gap between traditional techniques and modern innovations, drones are set to play an increasingly important role in IPM and the future of pest management (Table - 2).

4.3 Potential and Limits of UAS for Trichogramma Releases ✓✓

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The Trichocards offer some protection against both abiotic conditions and predation While Trichocards can be installed under any weather conditions, UAS have some constraints regarding mainly winds and their flight duration is limited by the battery autonomy. The regulations surrounding the use of UAS can also have an impact on its use for biological control applications. A tight timing of the UAS bulk release right before parasitoid emergence could offer a good solution, although the costs of parasitoids emerging too early would be even more detrimental. Releasing capsules containing the biocontrol agents could also offer parasitoids a protection. Bulk releases allow the dispersion of parasitoids during release while capsules act more like Trichocards where the parasitoid dispersal comes from punctual points instead of spreading in the field/forest.

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Trichocards and capsules also require more work, which of course adds to costs. However, preparing capsules is faster than preparing Trichocards, given that the proper installations are available. Of course, UAS also carry operation costs, that may vary based on whether they are done by producers, forest managers, or by service providers. UAS also brings the benefit of being potentially coupled with imagery that could detect the presence of the pest, and more precisely release biocontrol agents only on the specific part of the field/forests that need them, avoiding non-host or healthy plants.

- ACTUATION DRONES AGRICULTURE

IN

INDIAN

In the rapidly evolving landscape of Indian agriculture, the adoption of advanced technologies is becoming increasingly critical to meet the challenges posed by growing food demand, climate change, and resource constraints [55]. Actuation drones, a key innovation in precision pest management, offer transformative potential by enabling targeted and efficient application of biocontrol agents. These drones, equipped with sophisticated sensors and release mechanisms, can precisely distribute natural enemies, such as predators and parasitoids, directly to pest hotspots, reducing the need for chemical pesticides and enhancing the sustainability of agricultural practices [24]. In India, where smallholder farmers often struggle with the high costs and environmental impacts of conventional pest control methods, actuation drones present an opportunity to improve crop yields and reduce losses [56]. By facilitating the application of biological control agents, such as Trichogramma, drones can help manage pests like the fall armyworm and cotton bollworm, which pose significant threats to major crops. Additionally, drones can be utilized for the precision release of biopesticides, further minimizing environmental harm and protecting beneficial organisms [29]. However, the widespread adoption of actuation drones in Indian agriculture faces several challenges, including regulatory hurdles, high upfront costs, and the need for specialized training. Regulatory frameworks governing drone usage in agriculture are still evolving, with requirements for certifications, operational approvals, and adherence to safety standards.

Overcoming these challenges will require concerted efforts from policymakers, industry leaders, and agricultural extension services [57].

5.2 Disadvantages 1. High Initial Costs: The acquisition of drones and related equipment can be expensive, posing a barrier for small-scale farmers. 2. Specialized Training: Operating drones for pest management requires specialized training, which may not be readily available to all users. 3. Regulatory Challenges: Compliance with regulations governing drone use in agriculture varies by region and can be complex, potentially limiting widespread adoption. 4. Technical Limitations: Factors such as weather conditions, flight endurance, and payload capacity may restrict the effectiveness of drone applications in certain environments. 5. Limited Research: While some progress has been made, more research is needed on drone application parameters, particularly for certain biological agents like entomopathogenic fungi. 6. Maintenance and Upkeep: Regular maintenance and technical support are required to ensure drones operate effectively, adding to operational costs [59,60].

The successful integration of drone technology in Indian agriculture will also depend on collaboration among key stakeholders. Government support, in the form of subsidies or incentives, can make drone technology more accessible to smallholder farmers. Additionally, partnerships between research institutions, technology providers, and farmer cooperatives can facilitate the transfer of knowledge and skills needed to optimize drone usage for pest management [58]. As India continues to modernize its agricultural sector, actuation drones have the potential to play a pivotal role in enhancing productivity, sustainability, and food security. By reducing the reliance on chemical pesticides and promoting precision biocontrol, these drones offer a forward-looking solution to the challenges of pest management in Indian agriculture. With the right policies, investments, and stakeholder engagement, actuation drones can become a cornerstone of modern pest management practices across the country [58].

5.1 Advantages 1. Precision Application: Drones enable precise distribution of biological control agents, biopesticides, and pheromones, reducing wastage and ensuring targeted application in pest hotspots. 2. Cost and Time Efficiency: Drone-assisted releases reduce labor costs and time spent on manual distribution methods, especially in large or difficult-to-access fields. 3. Environmental Benefits: By promoting the use of biological control and reducing reliance on chemical pesticides, drones contribute to environmentally sustainable pest management. 4. Coverage of Large Areas: Drones can cover extensive fields quickly and efficiently, making them suitable for largescale agricultural operations. 5. Adaptability: Drones can be programmed for specific tasks and adjusted based on real-time data, making them versatile for different pest management scenarios. 6. Reduction in Pesticide Drift: The precision of drones reduces the risk of pesticide drift, minimizing harm to non-target organisms and ecosystems.

- CONCLUSION The integration of drones into pest management practices represents a significant advancement in sustainable agriculture. Drones provide precision, cost efficiency, and environmental benefits, making them ideal for tasks such as the release of natural enemies, biopesticide application, and mating disruption. By addressing the challenges associated with drone technology, including costs, training, and regulations, the agricultural sector can unlock the full potential of drones for pest management. As research continues to evolve, drones are likely to play an increasingly important role in reducing the reliance on chemical pesticides and enhancing the effectiveness of IPM strategies.
- FUTURE PROSPECTS

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- Advancements in Drone Technology: Future developments in drone technology, including increased payload capacity, longer flight times, and enhanced automation, will improve the efficiency of drone-assisted pest management systems.

- Cost Reduction: As drone technology becomes more widespread, the cost of acquiring and operating drones is expected to decrease, making them more accessible to a broader range of farmers. 3. Integration with AI and Data Analytics: The combination of drones with artificial intelligence (AI) and data analytics could enable real-time monitoring and decisionmaking, further optimizing pest management practices. 4. Expansion of Biocontrol Research: Continued research on the application of various biocontrol agents using

drones will provide insights into best practices and improve the effectiveness of these agents. 5. Sustainability and Ecosystem Impact: Drones will contribute to more sustainable agricultural practices by minimizing the environmental impact of pest management and promoting biodiversity conservation. 6. Policy and Regulatory Frameworks: As the use of drones in agriculture expands, more streamlined and supportive regulatory frameworks will be necessary to facilitate their adoption while ensuring safety and environmental protection.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

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Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript. 11.

COMPETING INTERESTS Authors have interests exist.

declared

that

no competing 12.

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Review Article

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Drones and Possibilities of Their Using Piotr Kardasz1*, Jacek Doskocz1, Mateusz Hejduk2, Paweł Wiejkut3 and Hubert Zarzycki4 Klaster B+R&I ul. Piłsudskiego Wrocław, Poland International University of Logistics and Transport in Wroclaw, ul. Sołtysowicka, Wrocław, Poland 3 Lower Silesia Accelerator Technology and Innovation Sp z o.o., ul. Nowodworska, Wrocław, Poland 4 Wyższa Szkoła Informatyki Stosowanej we Wrocławiu, Wrocław, Poland 1 2

Abstract This article shows the drones and possibilities of their using. First there was discussed construction of the drone, which the most important elements are frame, propellers, engine, system of power the electronic control and communication system. A drone is powered by batteries, which is the major drawback, because it is exhausted after 15 minutes of flight, causing a decrease drone on the ground. The lithium-polymer batteries are used for powering the drones. Then there were compared the military and civilian drones on selected examples. Military drones differ from civil of size and drive. They are bigger and powered by internal combustion engines. Civil drones are driven by electric motors. Next there were shown the possibilities of using the drones. They can be used by the public services (like police, fire brigades, border guards), by army, in industry, for taking photos and filming, in delivering shipments. The article shows the danger connecting with using the drones. The main danger of using the drones is the fall of a drone from a great height, which may be due discharge of the battery, damage caused by weather conditions (low air temperature, precipitation), hitting

in an obstacle (tree, building, high-voltage line). Currently a lot of projects related to the development of power for drones are conducted like battery of grapheme, pure lithium anodes, and fuel cells. A very important risks associated with the extensive use of civilian drones is related with privacy and the rights of citizens.

Keywords: Civil drones; Construction; Drones; Lithium-polymers accumulators; Military drones; Risk assessment

Introduction Drones or Unmanned Aerial Systems (UAV - Unmanned Aerial Vehicle or UAS - Unmanned Aerial Systems) are the aircrafts, which are able to fly without a pilot and passengers on board. Drone Controlling is performed remotely by radio waves or autonomously (with a predetermined route). Drones do not have a specific size or type of a drive. They are often equipped with accessories used for surveillance and monitoring, in the form of the optoelectronic heads. The most important feature of the drones is that they do not need any additional infrastructure to quickly register and monitor a designated area or object. A significant advantage is the extremely short reaction time when it comes to commissioning and preparing the unit for a flight. The precursors of UAVs are aircrafts used primarily in the uniformed services - the army and the police. The first countries that started researches on UAVs were the United States, the United Kingdom, Russia, Germany and Israel. The first time an unmanned flying vehicle was used by the Austrians in August of 1849. At the time there were used the balloons (filled with explosives) which have been known for almost 150 years and which were be used as bombs [1]. One of the first creators of drones was Charles Kettering, who in collaboration with Elmer Sperrym, Orville Wright and Robert Milikanem created in 1915, the aircraft named “Kettering Bug”. It was a primitive automatic plane, which on the basis of sensors defined its height (by using a barometer), the distance traveled (based on the amount of engine spins) and the position [2]. In contrast, the first civilian aircraft was produced only in the 80s of the twentieth century in Japan at the request of the Minister of Agriculture, Forests and Fisheries [3]. Public drones differ from military in the size and the drive. They are smaller and they are driven by an electric motor (military are driven by an internal combustion engine). They are mainly used for photographing and filming [4].

Drone construction Drone is composed of two major systems: 1. Movement system 2. Control system. J Civil Environ Eng

Movement system Frame: The basic element of a drone is a frame, which should be maximum light. The classification of frame construction is mainly based on the number of arms. The possible solutions of frames construction are shown in Figure 1. Due to the number of arms and the motors used the drones can be divided into: 1. Bicopters – two engines, 2. Tricopters – three engines, 3. Quadrocopters – four engines, 4. Hexacopters – six engines, 5. Octocopters – eight engines. It is generally recognized that the construction with more arms allows for a more stable flight. The frame is made of carbon cloth 3K. Propellers and engine: The next components of a drone are engine and propellers. They constitute the main propulsion system of a drone and are subjected to the highest loads, therefore their durability is very important. The propellers change a torque (derived from the engine) for a work used for lifting the vehicle in the air [5]. Due to the propeller system in relation to the flight direction it can be divided into the following types: 1. + – One is the leading propeller (at least four propellers), 2. X – The most common construction, in which two propellers are leading (with an even number of propellers),

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be the engine to cope torque, which is required to propel propellers, into motion. In addition, it is important to balance each propeller before use to minimize vibrations generated by the unequal operation of the system. It is very important to choose the engine and propellers in such a way that drones could for as long as possible to

lift a given load (Figure 2). The brush engines are used very often for building drones. However, the experiences have shown [5] that using brushless motors improves durability, efficiency and reduces the consumption of moving parts. This allows for longer and less emergency work of the engines.

Figure 1: Possible solutions of frame construction.

- Y – Three arms stacked in the Y, where one or two arms can be leading, 4. V – Very rare arrangement in which two propellers lead onto outstretched arms,

The power of a drone: The residence time of the object flying in the air depends both on the type of drive and the type of power supply [6]. A drone is powered by batteries, which is the major drawback, because it is exhausted after 15 minutes of flight, causing a decrease drone on the ground. In general, batteries are the sets of two or more voltaic cells of the same type, providing a current that is stronger than a single cell. These can be divided into disposable batteries and electric accumulators that can be unloaded and loaded many times. In the batteries and accumulators complex chemical reactions occur in which, depending on the type of battery participates many chemical elements. As a result of chemical reactions the chemical energy contained in their active substances is converted into electrical energy. Batteries are defined as chemical current sources. The set of active substances and the electrolyte is the basis of chemical current sources action. This set functions in the form of a cell containing positive and negative electrodes and an electrolyte in individual sealed enclosure in the batteries and accumulators [7]. The cells are a source of direct current and in depending on the type of chemical reaction can be divided into: 1. Primary cells in which electricity generation followed by an irreversible chemical reaction.

- H – A very rare arrangement where the construction is based on the H-shaped with two propellers leading. In each of the above-mentioned construction can be mounted double propellers (at the top and in the bottom), which significantly increases the strength of the drone, and does not require the addition of another arm. Double propellers mounted on a smaller number of arms increases the strength of a drone allowing more lift capacity and insuring the parallel engine in case of a failure. Thus, the own weight of multicopter is reduced, the material costs are falling and the drone can carry a heavier load. The double propellers rotate in opposite directions, balancing one other the inertia force. The wings of drones can be divided also on adapted for rotation: 1. Clockwise (CW), 2. Counter Clock Wise (CCW) [5]. The wings are made of carbon fiber, plastic or aluminum, and are attached to each other by lamination (also used for attaching the drone extremities), which ensures optimum performance between the weight of the entire construction and mechanical durability [5]. Because of the engine and propellers must be replaced as their consumption, the periodic preventive inspections are carried out. The size of the wings is very important. The larger is the diameter; the lower is the speed, which contributes to a reduction of drone volatility. The larger the wing blades, the greater aerodynamic lift generated, also the pressure exerted on the propeller hub also increases and the forces deforming propellers are getting bigger. The bigger are the propeller blades the stronger must also J Civil Environ Eng

Figure 2: Construction of a lithium-polymer battery.

- They are not designed to be charged by any other electricity source. 3. Secondary cells in which electricity generation occurs by reversible chemical reaction and are designed to be charged by other electricity sources. The battery is a source of electrical energy generated by direct transformation of chemical energy, which consists of one or more primary cells which is not reusable, including the housing, the ends and marking. Accumulator (electric) is a chemical power source allowing the multiple storage and release of electricity as a result of reversible transformations of energy. This is a source of electrical energy generated by direct transformation of chemical energy, which consists of one or more secondary reusable cells [7]. The various kinds of bacteria and accumulators are used currently. The following battery can be distinguished: 1. Zinc-carbon (zinc-manganese with chloride electrolyte), 2. Zinc-mercury, 3. Silver-zinc, 4. Alkaline (manganese-zinc with alkaline electrolyte), 5. Lithium. To the lithium batteries include a lot of subtypes, which combines the use of lithium or its compounds as anodes. Among the compounds used on the cathode include minibars and safes manganese oxide (IV), thionyl chloride, sulfur oxide (IV), iodine, chromate (VI),

silver and others. Among accumulators are used: 1. Lead-acid, 2. Lithium-ion, 3. Nickel-iron, 4. Nickel-cadmium, 5. Nickel-zinc, 6. Nickel-metal-hydride, 7. Silver-zinc, 8. Zinc-air, 9. Lithium-polymer. The lithium-polymer batteries are used for powering the drones. They differ from them only some properties and parameters. The basic principle of operation, as well as the chemical reactions occurring in the cell is the same as in Li-ion cells. In the Li-ion cells the one of the electrodes is made of porous carbon and the second of metal oxides. The role of the electrolyte fulfills here complex lithium salts dissolved in a mixture of organic solvents. The most commonly used material for the cathode is LiCo2. In this type of accumulators the following reactions occur:

Al, Li-Si, Li4Ti5O12. The electrolyte is a lithium salt dissolved in organic solvents means (lithium perchlorate (LiClO4), dioxolane (C3H6O2)). This type of accumulators discharge at a slower rate than the devices using nickel and it is also lighter of them. The voltage obtained from them is higher. Lithium-ion accumulators must be recharged frequently, and immediately after unloading (in contrast to nickel accumulators). It is necessary to keep them in a cool place, because high temperatures can cause a decrease of their viability and in extreme cases an explosion of the battery. Li-ion cells have a relatively high operating voltage, containing in the range 4.1 - 2.5 V, while their nominal voltage is 3.6 V. The proper energy of commercially available Li-ion batteries is more than 150 Wh/kg. The maximum discharge currents may reach up to 5C, although in most cases it is not recommended to exceed the loads 1-2C. Coefficient of self-discharge of Li-ion battery is very small and they can be stored for several years without significant loss of capacity. They did not show a memory effect, and the temperature range in which they may work is extremely wide and range from -40 to 65°C [6]. From the user's perspective, Li-Po cells differ from Li-ion cells of the rated voltage (it amounts 3.7 V) and maximum (4.2 V). During using the batteries it is necessary to pay attention, that not to exceed the lowest (3 V) and the highest (4.2 V) allowed voltage on the targets. Characteristics of using the battery is non-linear, so the charging and discharging currents should not be exceeded. In addition, Li-Po cells have a higher resistance to mechanical damage than Li-ion, and they can work at much higher loads-up to 30C, depending on the cell type [6]. These batteries, unlike the conventional lithium-ion batteries with liquid electrolytes, use electrolyte in solid form, in which the essential components is the polymer with a lithium salt dissolved in it. The use of solid polymer increases the resistance of cells in the case of short circuit or overcharging and eliminates the problem of possible an electrolyte leakage, which significantly increases the safety of using these accumulators. For the lithium-polymer accumulators construction are used the lithium metal alloys and conductive polymers. Due to the presence of polymers the new technology enables the construction of flexible, very thin and flat flexible cells (even about millimeter thickness). However these cells are not resistant and easily damaged by even a small overcharging, so electronic circuitry controlling the charging process are very complex. The accumulators have a high energy density and relatively high degree of flexibility in the design of shapes and sizes. To ensure emergency-free and safe operation the accumulators or accumulators packs (series of cells) must be equipped with an electronic battery management system – BMS. Due to the extremely favorable ratio of volume to weight ratio and minimal self-discharge they are a very attractive a power source in model building [7,8]. Classic electrochemical accumulators, despite the increase of their specific energy in recent years do not provide the basic requirement, which is a long residence time of a drone in the air [6] From the user's perspective, used electrochemical accumulators should be characterized by: 1. Small sizes, 2. Small mass,

$LiMO2 \rightarrow Li1\text{-}x\ MO2 + xLi^{+} + xE$

- Fast loading time,

$xLi^{+} + xe^{-} + C \rightarrow LixC$

- High safety of using,

where, M = Ni, Co, Mn

- High durability,

A positive electrode constitute the metal-oxides of lithium, LiXMn2O4, LiXCoO2, LiXNiO2, the mixture of MnO2 i Li2MnO3. A negative electrode constitutes a special graphite or electrode made on the basis of amorphous tin oxide, and also are used the alloys of LiJ Civil Environ Eng

- Negligible phenomenon of self-discharge, 7. Low price. The above features make, that at the possible smallest volume, at

the possible low weight we can obtain a source of electricity with high energetic efficiency. And the possibility for fast charging allows in a short time supplement the energy in the accumulator [6].

Military drones differ from civil of size and drive. They are bigger and powered by internal combustion engines. Civil drones are driven by electric motors [14-19].

The electronic control and communication system

Civil drones: One example is the DJI Phantom Vision 2, which is used for photography and video filming. The mass of the airplane battery is 1160 g. A lithium-polymer cell with a capacity of 5200 mAh for driving the four rotors allows for 25 minutes of continuous flightwith with the recording. The control is performed over the air waves with a frequency of 5.8 GHz using the remote control. The effective control range is 300 m, and using signal amplifiers even 1000 m. Thanks to the Wi-Fi module the synchronization the device with a phone or tablet is possible, which increases the possibility of modifying settings for drone in flight, such as the size or resolution of the recording multimedia, information about the status of the machine (battery status, connection to GPS altitude speed). It is also possible the preview of the camera view “live”, recording and downloading videos and photos during the flight. The GPS receiver with software provides a standalone return to the starting point in case of losing the connection with the controller. Drone also recognizes areas, where flights are prohibited (proximity to the airport) and inform the controller about it. The heart of the drone is a camera with photos resolution of 14 Megapixels, filming of 1080p, diagonal of the matrix 1/2.3”and the field of view of 110°/85°. Photos are saved in formats .JPEG and .RAW, which facilitates their interpretation. After equipping the drone with a camera of different type and the appropriate software, the camera can be used to map areas difficult to access [4].

The control system is responsible for the drone fly up, down; rotate, for his reaction to the emerging forces and for stability. Most of the control systems are equipped with the same set of sensors with the difference in the speed of calculations and in algorithms used. The control system consists of [4]: 1. Flight controller, responsible for machine control capabilities, 2. ESC (Electronic Speed Control) –the unit responsible for engine rpm, 3. Supplying plate, separating the power supply for regulators turnovers and motors, 4. Sim module, which allows the transmission of telemetry data, 5. Proximity camera - an element of anti-collision system, 6. The numeric keypad to enter the customer PIN codes. Controllers engines are used to ensure maximum performance and the highest level of fail safety. Controls should be selected, so that their parameters correspond to the maximum current consumption of the motor, which shall ensure the maximal parameters of drives. Some controllers have additional exit type BEC (Battery Eliminator Circuits), thus it is possible to supply the control system with the voltage of 5V and efficiency of 2A [9-13]. This provides good working conditions of control system. Limited is also the complexity of the control board. The controller also controls the condition of the battery. When the battery voltage drops to low levels, it forces a reduction in engine RPM, preventing the damage of battery. It provides additional security when the control unit will not work. Programming the controllers is carried out using a programming card, thanks to which it is possible to change the parameters of the devices - the voltage level of a power cut, and how to start up the engine [5]. During the designing process of the control system must first pay attention to the correct power to the controller and establishing communication by the programmer. In a further step it is needed to include the necessary filtration power (capacitors and choke) and protection of the pin analog-to-digital converter. The digital transducer serves as a voltage meter and its conversion into digital form, understandable for the controller. By measuring the voltage at every cell we can gain information about the battery charge [5]. In study [5] for controlling the motor rotary speed was used a mechanism PWM (Pulse Width Modulation) or pulse width modulation. It is possible using this method to obtain different average voltage. At this project we use Bluetooth communication between the controller and smartphone with Android operating system [5]. Android is now the most popular operating system in the world for mobile devices. It is distinguished by openness, small hardware requirements, simple configuration and easy transfer between different mobile devices. This has contributed to the preparation of an application that allows controlling the drone from the level of smartphone. This allows for data transmission up to 100 m. To start flights control unit must know the location of the machine in space, which allows the measurement module, containing a gyroscope and accelerometer, which communicates with the

controller via the I2C bus. The gyroscope allows tracking the flight of the object, and accelerometer allows the drift of the module and determines the absolute point of reference. Drone control is done by varying the speed of the respective motors. The control algorithm is necessary to stabilize the machine in air. Comparison of military and civilian drones on selected examples. J Civil Environ Eng

Military drones: An example of the military drones is MQ-1 Predator (M- is a multirole aircraft, Q mark the drones), which belongs to the UCAV (Unmanned Combat Aerial Vehicle). In the apparatus emphasis is placed on tools for observation. There was used the cameras with a very high resolution, thermal imaging and the infrared. Components of the drone are as follows: 1. Rotax four-cylinder engine with 115 horsepower, 2. Communications antenna Ku-band, 3. Two internal GPS antenna and GPS navigation system, 4. Sets of fuel cells, 5. Set of cameras and encoders, 6. Transmitter, receiver and radar antenna slot. •

It is part of the whole set which includes:

- Four drones type of RQ-1 or MQ-1, 2. Ground control station usually placed on a truck, which housed the position of the pilot, the operator of sensors or weapons and an antenna with a diameter of 6.1M with accessories. This enables communication between drones and ground control station. The advantage of predators is their easy transport, because they can be disassembled into six parts [4]. Comparision of the drones: Table 1 describes the comparison of the two types of drones.

Specifications and possibilities of using drones Legal regulations Polish law very little said about drones. The act “Aviation Law” of the 30 June 2011 tells about the “model aircrafts and unmanned aerial

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DJI Phantom View 2

Size (length x width x height)

GAAS MQ-1

0.29 x 0.29 x 0.18 m

8 x 12 x 2m

Unladen/start mass

1.36/2.6 kg

512/1020 kg

The length of the flight

25 min.

24-40 h

Drive type / kind

Electric / Propeller

Diesel/Propeller

Type of engine

Four electrical engines

Four pistons engine Rotax 914 (115 KM)

Range

0.7-1 km

726 km

Maximum speed

54 km/h

217 km/h

The length of the runway

0 m (vertical takeoff)

1500 m

Crew

1 person

2-3 persons

Price

ok. 800 $

4 mln$ /20 mln$1

cost of 1 drone/cost of system (4 planes, ground control station, satellite dish with accessories) Table 1: Comparison of the drones.

archaeological, advertising purposes etc. With its small dimensions and high maneuverability they can operate the flights between obstacles, buildings, and even are able to fly to rooms, through the open gates, windows and doors. Models equipped with thermal and night vision cameras (using the infrared active or reinforcing starlight) can be used as prospecting machine in rescue operations, with a daily patrolling of the chosen area and can operate round the clock above the woody areas [20-25]. They transmit an image in a real time allowing on an immediate reaction of relevant services in case of emergency, an accident or a crisis situation requiring intervention. They can be used by the following services, industry and companies: a) Fire brigade: 1. Vision support in actions of fighting forest fires, of flood, road, rail and air disasters

vehicles with a maximum take-off weight not more than 25 kg used exclusively for operations in sight". According to the Act:

- Thermal imaging the directions of conducting of fires,
- In the case of a drone with a weight not exceeding 25 kg, it is possible to conduct recreational flights and sports in sight of the operator. To perform such flights do not need a license, permit or insurance.
- Tracking and monitoring the sources of pollution,
- To perform commercial flights of drones not exceeding a mass 25 kg in sight, it is necessary to have a qualification certificate provider, medical tests flights and civil liability insurance.
- Communication disasters service,
- Flights ships weighing over 25 kg must be reported to the CAO in order to obtain permission for flights.
- Traffic congestion documentation and traffic jams,
- Flights out of sight of the pilot can only take place in specially separated zones.
- Thermal detection of fire sources, 5. General support of the movable operating position/command. b) Police: 2. Patrolling a designated area, 4. Operation and monitoring of mass events,
- The law in other countries differs greatly from Polish. In the UK, are permitted the flights: 6. Drones weighing up to 20 kg, 7. At a distance of not less than 150 m from cities, population centers and 30 m from the people, 8. With the subscription of OC insurance, 9. In the case of commercial flights the registration, the consent and release the pilot is necessary, 10. Out of sight only in certain areas. In the United States, the following provisions shall apply:

Figure 3: DJI PhantomVision 2.

- It is possible to perform flights only after receiving a permit issued by the local aviation authorities, 2. Special facilitations in the granting of licenses are entitled to services such as fire, police, and scientific community, 3. To carry out commercial flights is impossible. In the near future it can be expected, that the Aviation Law will be adapted to the current state of technology. For the companies interested in commercial use of UAVs the flights out of sight (with the fulfillment of additional conditions) will be very important. (Figures 3 and 4)

Posibilities of using the drones Unmanned units are the ideal devices to patrol large areas, so they can be used to protect property and the protection of state borders. They can also perform aerial photographs used for geodesy, J Civil Environ Eng

Figure 4: MQ-1 Predator.

- A support for pursuit actions, searching and other police actions, 6. Obtaining the evidence. c) Border guards: 1. Monitoring the border areas,

threat to the drone, due to its value is the people. It can be stolen. In this situation, it may be helpful the localization function and recognizing the situation. Change of the machine course can indicate about the theft. At this case, the drone can begin to take pictures using cameras (sensors) and give a beep deterrent the thief and focusing attention of witnesses [4].

- Reconnaissance and surveillance area,

A very important risks associated with the extensive use of civilian drones is related with privacy. These devices have the ability of following for the tracked object and to observe it from many different perspectives. They can be equipped with cameras, night vision devices and various sensors, facilitating snooping. While their wide using by municipal services (including the police) to control the civilian population, could pose a serious danger to human rights. Potential risks associated with the widespread use of drones require the use of complex solutions and the introduction of deliberate regulation aiming at effective protection of citizens' privacy [31-35].

- Direct support for fighting and training tasks,

Summary

- Conducting the shares of intelligence,

Summing, limited use of drones is largely related to the short time of flight, associating with the discharging of the battery powering it and the necessity of recharging. Undoubtedly a big obstacle in the use of drones is mentioned earlier risk of privacy and the rights of citizens. Currently a lot of projects related to the development of power are conducted. One of them is a project of the battery of graphene, which is run by California Lithium Battery. It distinguishes with its high-speed charging, biodegradable and lightness. Another example is the use of pure lithium anodes, which may result in a fourfold increase in battery capacity maintaining the same size and weight [36-39]. You can also consider the use of internal combustion engines as main-propelling the propellers or auxiliary to charge the batteries on the fly. An alternative to the lithium polymer accumulators is the power of drones by fuel cells. In this type of cells electrochemically active substances taking part in the electrode processes are supplied from the outside to the cell and the reaction products are taken to the outside [40]. Therefore the fuel cell works as long as there is provided the fuel (typically hydrogen) and an oxidant (usually oxygen from air). The process of energy conversion overlaps in one stage (direct conversion) and leads to the production of electricity, waste heat and water. The fuel cells system weighs above 3.5 times less than the battery lithium-ion cells with similar parameters. Due to the much more favorable parameters of energy density the attempts are carried out to replace previously used cells (eg. of lithium polymer) with fuel cells [6]. Due to the fact that in unmanned flying apparatuses lengthening of flight time is a critical factor in many cases, there are made the attempts to use fuel cells.

- Air supporting of control traffic border, 3. Fast visualization of the area and mapping, 4. Detection and monitoring of pollution sources objects, land and water border, 5. Tracking moving targets. d) Army:
- Tracking a moving target, 5. The fight against terrorism. e) Energetic and chemical industry: 1. Monitoring, diagnostics and analytics of level gases emission, fumes and other harmful or undesirable substances, 2. Thermal detection of fire sources, 3. Monitoring of production, technology and logistic processes, 4. Control of infrastructure of the determined area. f) Geodesy companies: 1. Fast visualization and control of area, 2. Mapping. g) Advertising Businesses: 1. Spots, 2. Photos I advertising films, 3. Promotional materials. 4. Drones have also a bigger use in delivering shipments.

Risks associated with the use of drones The use of drones on a large scale entails a high risk. The main danger is the fall of a drone from a great height, which may be due to: 1. Discharge of the battery, 2. Damage caused by weather conditions (low air temperature, precipitation), 3. Hitting in an obstacle (tree, building, high-voltage line). These risks can be predicted; therefore the action should be taken to prevent their uprising. The battery status and other telemetry data, including temperature can be controlled remotely by the system. In case of exceeding the one of the parameters the alarm should be launched. This will allow take the action, such as emergency recall the drone to a branch. However, the sensors and software that based on the flight path and on the detected obstacles continuously update the route are responsible for the avoidance of obstacles [26-30]. A serious J Civil Environ Eng

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AGRICULTURE

Editorial

The Rise of the Drones in Agriculture Frank Veroustraete* Department of Bioscience Engineering, University of Antwerp, Belgium

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Figure: 1.

Introduction Drones Create the Expectation of a Large Swing in the Way We Grow Crops For years now, drone advocates have cited precision agriculture - crop management that uses GPS and big data - as a way to increase

crop yield while resolving water and food crises. Unfortunately, drones haven't had a significant impact on agricultural practices, at least

until recently. A lot is happening lately on the subject of drone applications in agriculture and precision farming. From the ability to image, recreate and analyze individual leaves on a corn plant from 120 meters height, to getting information on the water-holding capacity

of soils to variable-rate water applications, agricultural practices are changing due to drones delivering agricultural intelligence for both farmers and agricultural consultants.

Unfortunately, many of the promises being made to farmers, drone service providers simply couldn't deliver, even backed up by

proper research yet. Until now airspace controllers did not open segments of airspace above agricultural areas for commercial drone agricultural research to take place. A shift in regulatory policy in this respect allows certified drone service provider firms - many of which

are in a start-up phase - to assist both large and small farming operations with water and disease management and a charge for these services. The service providers - with an open airspace to a specific flight height will also be able to use drones to provide better planting

and crop rotation strategies and to provide a higher degree of all-around monitoring of how crops are progressing on a day-to-day basis in different parts of a given crop field, as well.

In the coming years all of the possible uses for drones will be fleshed out by drone service providers and farmers itself. A boost in crop

intelligence will make farms more efficient and help smaller operations compete with their more well-heeled Big Agriculture competitors.

Citation: Frank Veroustraete. "The Rise of the Drones in Agriculture". EC Agriculture 2.2 (2015): 325-327.

A widely-cited drone report released by the Association for Unmanned Vehicle Systems International predicts that the legalization

of commercial drones will create more than €70 billion in economic impact (such as revenues, job creation) between 2015 and 2025, and that precision agriculture will provide the biggest piece of that growth. For now here are five drone agricultural applications already being implemented in the field.

Drone Applications in Agriculture Mid-Season Crop Health Monitoring The ability to inspect in-progress crops from about 100 meters height using Normalized Difference Vegetative Index (NDVI) or near-infrared (NIR) sensors is, thus far, the premier application for drones in farming. This was a task traditionally performed by often-reluctant college interns walking into the fields with a notepad. Drones from the present generation, allow for coverage of more surface area

in a much shorter time stretch, as well as the capturing of data that cannot be seen by the human eye (like the NDVI or near-infrared). Moreover, it removes much of the human error aspect of traditional inventory work, though a physical inspection of an area of concern after viewing the imagery is still recommended.

Irrigation Equipment Monitoring

Managing multiple irrigation pivots is well...., it is laborious, especially for large growers with many fields spread out across a county

or region. Once crops like corn begin reaching certain heights, mid-season inspections of the nozzles and sprinklers on irrigation equipment that deliver the much-needed water really becomes a painstaking exercise.

Mid-Field Weed Identification

Using NDVI sensor data and post-flight image processing to create a weed map, farmers and their agronomists can easily differenti-ate areas of high-intensity weed proliferation from healthy crop areas growing right alongside them. Historically, many farmers haven't realized how pronounced their weed problem is until harvesting was performed.

Figure: 2.

Variable-Rate Fertility Though many will argue that ground-based inspections combined with satellite imagery, along with a dedicated grid soil sampling

program is more practical for the purpose of refining Nitrogen, Phosphorus and Potassium applications in agriculture, drones do have their fit. A drone service start-up company in the US has used NDVI maps to direct in-season fertilizer applications on corn and other

crops. By using drone-generated, variable-rate application (VRA) maps to determine the strength of nutrient uptake within a single field,

the farmer can apply 300 kg/ha of fertilizer to struggling areas, 200 kg/ha to medium quality areas, and 150 kg/ha to healthy areas, decreasing fertilizer costs and increasing yield.

Cattle Herd Monitoring

Many growers during periods of depressed commodity prices made the call to diversify their farms by adding cattle or swine opera-tions. Drones are a solid option for monitoring herds from overhead, tracking the quantity and activity level of animals on one's fields. They are especially helpful for night-time monitoring due to a human's eye's inability to see in the dark.

Citation: Frank Veroustraete. "The Rise of the Drones in Agriculture". EC Agriculture 2.2 (2015): 325-327.

Conclusion

As conclusion, it can be stated that as the calendar starts to turn to 2016, the examples given in this Editorial are current and common uses for drones in precision agriculture. This application list is bound to undergo quite some growth in the near-future as more and more research takes place and will take place and certainly when in the European Union, airspace will be opened for certified drone equipped agricultural service providers.

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Citation: Frank Veroustraete. “The Rise of the Drones in Agriculture”. EC Agriculture 2.2 (2015): 325-327.

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Technical Discussion Paper on

DRONE USAGE FOR

AGROCHEMICAL SPRAYING

JULY 2020

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Introduction Drones have proven to be among the most promising technologies emerging from the Fourth Industrial Revolution. Unmanned aircraft systems (UAS), commonly referred to as drones, are democratizing the sky and enabling new participants in aviation. Indian agriculture is yet to reap the full bene ts of the economic reforms initiated in 1991. In addition, they are faced with structural challenges that include fragmented landholdings, lack of adequate market connect, rising costs (especially of human labour), poor/ below par yields in most crops and – not the least – low usage of modern technology relative to their counterparts in the US, Europe, Brazil, Argentina or China. Satellite-driven technology, big data analytics and digital solutions are helping farmers in many countries today to make better and more informed cropping decisions with regard to weather changes, soil nutrient application, and pest and disease control. Many of these technologies are likely to be introduced in India over the next few years. One area, which can have a major impact on our farms and needs quick government intervention is the use of drones for spraying of agrochemical products. The objective of this Technical Discussion Paper is to recommend that Indian Government develops a regulatory framework for deploying drone in agrochemical spraying based on best practices. The main bene ts of drones in agrochemicals are the following: •

Increased efficiency and precision of agrochemical application that, in turn, leads to improved pest management and crop productivity and eliminate or reduce wastage of CP products.

•

Signi cant reduction in risk of operator exposure during spray operations

•

The eld capacity of drone-assisted spraying is about 20 times higher compared to that of manual spraying

•

Lower water consumption

•

Development of certi ed applicators, including community spraying professionals providing application services, thereby creating new skilled employment and entrepreneurship potential in rural India

Benefits of drones for pesticide application

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Asian Scenario Drones in agrochemical application have, in just a few years, grown in sophistication and scale, boosting the ease, con dence and affordability of use. The good news is that this innovation is being driven largely by Asia. The adoption of drones in farms is the highest in countries such as China, Korea and Japan, which are also confronting growing labour shortage challenges from urbanization and aging populations •

According to a study by Goldman Sachs1, the agriculture sector is predicted to be the 2nd largest user of drones in the world by 2021.

•

As per a study by Food and Agriculture Organization of the United Nations2; in China alone, the number of agriculture drones is estimated to have doubled between 2016 and 2017, reaching 13,000 aircrafts and 30M hectares of crop land was sprayed by drones in 2019.

•

The economies of scale in usage have meant that the operating costs per hectare in some Asian countries are now equivalent to just Rs. 100 - 150 for eld crops (rice, wheat and maize) and Rs. 250 - 400 in orchards.

Indian Scenario Indian Agriculture has gone through many advancements and bene ted by research and adoption of new technologies by farmers. Technologies like drip irrigation, mechanized farming for planting and harvesting are being successfully used for sustainable agriculture in India. In recent years, use of drone in agriculture has gained lot of attention on digital space including its use as an alternative equipment for spraying. The intelligent use of UAV technology can help ght highly mobile invasive pests such as Fall Armyworm (FAW) and desert locusts more efficiently and effectively; prevent them from becoming endemic and reduce the cost of production while maintaining high agricultural productivity. Recently Government of India, as a special case has recommended usage of drones for spraying operations to control the locust as band application and save the crops, where certain State Governments have issued e-tenders for the inclusion of drones in aerial pesticide applications. Ministry of Agriculture3 has come up with broad speci cations for drones that can y at night and stay airborne for night duty in locust ight, making India the rst country to do so. While the safety and exposure of operator during application of Crop Protection Products (CPPs) have been a concern, labor shortage and economics of crop protection are emerging issues. Use of drone for spraying with proper training of operators and use of PPEs would offer many advantages, which calls for looking at this technology in more holistic way considering its bene ts.

1

For more details please refer - h ps://www.goldmansachs.com/insights/technology-driving-innova on/drones/ ;Neha Chamaria, 'Drone Usage in Agriculture Could Be a $32 Billion Market', Fox News Business, 25 November 2016. Available at h ps://www.foxbusiness.com/markets/drone-usage-in-agriculture-could-be-a-32-billion-market 2 Gerard Sylvester (Edited),'E-Agriculture in Ac on: Drones for Agriculture'Food and Agriculture Organiza on of the United Na ons and Interna onal Telecommunica on Union, Bangkok, 2018. Available at - h p://www.fao.org/3/I8494EN/i8494en.pdf 3 Alnoor Peermohamed, 'Agriculture ministry eyes drones to fight off locusts swarms', The Economic Times, 29 June 2020. Available at - h ps://tech.economic mes.india mes.com/ news/technology/agriculture-ministry-eyes-drones-to-fightoff-locusts-swarms/76681156

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Use of Drone for spaying CPPs will overcome the challenges faced in current conventional sprays as follows: Challenges with Conventional Spray

Bene ts by using Drones for Spraying

Ÿ Laborious, time consuming and less

Ÿ Convenient, fast and highly efficient.

efficient. Ÿ Operator pesticide exposure can occur

Ÿ No / minimal exposure during spraying.

during application using backpack or tractor sprayers Ÿ Improper application and non-uniform

Ÿ Autonomous ight capacity with

coverage caused by backpack application that requires a moving spray wand, maintaining a consistent walking pace, and in uenced by human

consistent speed, ight stability, and RTK/GPS capability provides precision spray with uniform coverage.

Ÿ When there is sudden pest/disease

Ÿ In case of sudden pest/disease

outbreak, farmer's ability to complete an application may be slow resulting in suboptimal crop protection

outbreak, spraying operations can be done efficiently and acreage covered quickly in a short period of time.

Ÿ Unskilled and novice operators

Ÿ Trained and certi ed operators

Ÿ Low ROI (time consuming, more water

Ÿ Better ROI (Return on Investment)

consumption, increasing labor cost)

offsetting the high operational cost

Ÿ More water consumption

Ÿ Less water consumption

Ÿ High variation in accuracy delivering

Ÿ Low variability in accuracy delivering

labeled product rates.

labeled product rates.

Drone use Regulations – Global Scenario: •

Use of Drone for spraying crop protection products offers more bene ts and is suitable equally for smallholder farms as well as the large farms; it is gaining more popularity in Asian countries.

•

Japan has an extensive 30 years of experience using single rotor remote-controlled helicopters (unmanned drones) for spraying crop protection products and have well established guidance document.

•

Similarly, use of Drone for spraying crop protection products is regulated in South Korea and Malaysia. China has established a civil aviation law and SOP, tolerating chemical spray applications of conventionally registered products while ne tuning the guidance. In other countries such as Philippines, Indonesia, Thailand, Taiwan etc. the guidance documents are under development.

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Latin American countries are commercially using drones in small scale and also determining suitability for multiple crops.

•

In the USA, the EPA (Environmental Protection Agency) allows the use of pesticide application using drone technology when in compliance with federal aviation rules and if manned aerial application is present on the label.

•

The European Union, known for their restriction of manned aerial application, is now considering the use of drone pesticide application. The EU is developing guidance for use of Drones for spraying CPPs for areas inaccessible to vehicles and where manual spraying is difficult e.g. Grapes orchards on sloppy hills. Recently, Switzerland has approved use of Drone for spraying on agriculture crops.

•

Australia and New Zealand have embraced Drones technology and are governing the use of drones in Agriculture and management of weeds.

Drone use Regulations in India In India usage of drones for military purposes started during 1999; however in 2014, India imposed a sudden ban on the use of civil drones. Ministry of civil Aviation, Government of India published a regulatory policy regarding the use of drones in 2018. The Directorate of Plant Protection, Quarantine & Storage, Faridabad issued 'Standard Operating Procedures (SOP)' 4 on aerial spraying using aircraft/helicopter/drone for control of Desert Locust th on 18 May 2020 (please refer Annexure- 6 on point-wise comments from CropLife India). While on the other hand, the Ministry of Civil Aviation issued Draft Noti cation on 'The Unmanned Aircraft System Rules, 2020' 5, on 2nd June, 2020 We strongly believe, that it would be in the interest of farmers and the Agriculture in India if drone technology can be deployed on a large scale for agrochemical applications. This should be supported by a robust and pragmatic science-based policy framework; with Japan's revised guidance document serving as the most suitable point of reference, while drafting our guidance documents. The focus should be to minimize the potential risks by promoting active learning and rapid adoption of this well-developed & globally extensively tested technology. Principles for Building a Sound Regulatory Framework

1 2 3

Local civil aviation laws: Operating under the umbrella civil aviation law, vehicle speci cation are regulated by the competent authority Standard Operating Procedure (SOP) for the Safe Use of Drones for Pesticide application: Safety during spray operations is enforced within pesticide regulations setting piloting requirements and safe use practices Premission for spray operation: Product approval for spray operations may refer to existing spray-registrations and established or amended regulatory procedures

4

For more details please refer to - h p://ppqs.gov.in/divisions/locust-control-research/important-informa on; h p://ppqs.gov.in/sites/default/files/sop_on_aerial_spraying_including_use_of_drones_0.pdf 5 Dra The Unmanned UAS Rules, 2020, Ministry of Civil Avia on. Available at h ps://www.civilavia on.gov.in/sites/default/files/Dra _UAS_Rules_2020.pdf

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The rst step in establishing a robust policy framework is to identify & minimize the various risks associated with drone application and the processes and procedures to deal with them. These cover the speci cations for the drones (unmanned aerial vehicles or UAVs) and the product formulations being used, the capabilities and training standards of the spray operators, and environmental variables. Based on these, a Standard Operating Procedure should be put in place for spray operators, drone manufacturers and agrochemical companies to comply with (Annexure- 3). It is worth looking at Japan and borrowing from their requirements, both for licensing of UAVs and operators as well as product registration for drone spraying, as stipulated in the country's most recently revised 2019 guidance document. Having one of the longest histories in the use of UAVs

– particularly, remote controlled helicopters (RCH) – for spraying of agrochemicals and with over 30 years of data generation, Japan provides the strongest point of reference for regulators to frame the appropriate rules and SOPs. Keeping the above points in background, the following needs to be considered prior to drafting a guidance document •

The necessary regulations should take into consideration (1) civil aviation laws (both local and umbrella) and setting of vehicle speci cations, (2) SOPs and piloting requirements for safe use of drones, and (3) product approval and permissions for spray operations.

•

In addition to these general regulations, we would recommend at least ve other criteria to be met for obtaining permission: (1) approval of vehicle needs, (2) licensing or certi cation of pilots/operators and training for agrochemical application by drones, (3) registration of agrochemical product sought to be sprayed, and (4) Encouragement for fast approval of ULV formulations or allowing mixing of mineral oils to the existing formulations, so as to serve the purpose of ULV formulations, however, by proper testing of ash point (5) Strict adherence to product label instructions (depicted in annexure 2).

•

More speci cally, we propose6 setting up a system for certi cation or licensing of drone operators to ensure their capability to pilot the UAV machines safely. Such certi cation/licensing should be subject to regular renewal and conducting of refresher courses. The authorities should also accredit training facilities to put in place a standardized programme for all agricultural drone operations.

•

The Product Registration Process for inclusion of drone as alternate equipment for application of CPP must be simpli ed & time-bound and should not be duplicated from scratch as the drone use is just an extension in the case of a formulation already approved for conventional manual spraying. The idea is to reduce registration timelines and make available the same crop protection products to farmers quickly, without compromising on safety and efficacy. A reasonable and predictable timeframe for all the regulatory clearances will create a vibrant and a compliant ecosystem that attracts more investment in the sector.

6

Asitava Sen ' Flight to Safety', The Indian Express, March 12, 2020. Available at h ps://indianexpress.com/ar cle/india/flight-to-safety-the-case-for-drones-in-spraying-agrochemicals-6310121/

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Japanese guidelines stipulate that the bio-efficacy and maximum residue limits data for drone/UAV applications be considered equivalent to that of conventional spraying, so long as the critical parameters (active ingredient dose per hectare, pre-harvest interval and number of applications/sprayings) are within a determined range. There is no need, therefore, for any separate UAV bio-efficacy and residue trials, even if an additional crop safety study might be required in some conditions.

Japan: Registration requirements of pesticides by drone application Type of date requirement

Label extension of registered formulation from conventional application to UAV application

New formulation for UAV application

Bio-efficany data

Exempted if pest/disease claim and critical GAP (Crop, Dose PHI) is within the range of existing registration. If not, full data requirement

Full data requirement by UAV application

Crop residue data

Exempted if critical GAP is within the range of existing registration. If not, full data requirement

Exempted if critical GAP is within the range of existing registration

Crop safety data

Full data requirement by UAV application

Full data requirement by UAV application

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Potential Risk & Mitigation Strategy 1.

Identifying and mitigating the potential risks associated with drone application in spraying of crop protection products is an important aspect. These include risks to the operator, bystander, the crop itself as well as the environment.

2.

The potential mitigation measures used globally cover: a.

Use of duly approved remotely piloted aircraft systems (RPAS)

b.

Agrochemical formulations being used

c.

Capabilities of the pilots and operators

d.

Environmental variables

3.

Given these aspects, spraying operations should be permitted only for authorized drone spraying entities under certi cation / license from the regulatory authorities and must adhere to the policy and guidelines issued from time to time. In addition, the RPAS itself must comply with the Indian regulations as required by the Government.

4.

In some provinces of Australia, aircraft pilots and companies operating in the domain of chemical spraying on agricultural lands are required to possess licenses7. Moreover, such aircraft pilots are mandatorily required to have undergone necessary training for such operations8. Such relevant regulatory requirements mandated by governments in different countries must be studied and incorporated in preparation of risk mitigation strategy and SOPs with respect to spraying of CPPs through UAV platforms in India.

5.

We propose that FICCI Committee on Drones and CropLife can jointly coordinate consultations with all stakeholders including various ministries9 and agencies. Such deliberations shall be most useful to ferret out genuine concerns and prepare comprehensive guidelines, best practices and standard operating procedures for such operations.

7

Using chemicals responsibly', Northern Territory Government, Australia. Available at h ps://nt.gov.au/industry/agriculture/farm-management/using-chemicals-responsibly/spray-applicator-licences 8 Aerial distribu on of agricultural chemicals', Queensland Government, Australia, Available at h ps://www.business.qld.gov.au/industries/farms-fishing-forestry/agriculture/land-management/chemicalcontrols/aerial-distribu on ; 'Agricultural Chemicals Distribu on Control Regula on 1998', Queensland Government, Australia, Available at - h ps://www.legisla on.qld.gov.au/view/pdf/inforce/current/sl-1998-0135 ; 'Agricultural And Veterinary Chemicals (Control Of Use) Act 2004', Northern Territory Government, Australia, Available at h ps://legisla on.nt.gov.au/en/Legisla on/AGRICULTURAL-AND-VETERINARY-CHEMICALS-CONTROL-OF-USE-ACT-2004 9 In case of Israel, the regula ons on aerial spraying of pes cides were shaped by mul ple ministries. For more details see – 'Natural Resource Aspects of Sustainable Development In Israel', Submission of Israel at the 5th Session of the United Na

ons Commission on Sustainable Development, 01/04/1997. Available at h ps://www.un.org/esa/agenda21/natlinfo/countr/israel/natur.htm

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Potential Risks Associated with Drone Operation

Risk Category Vehicle Risk

Guidance

Measures Ÿ Permits for UAVs meeting

Ÿ Civil Aviation

de ned speci cations Flight Operations

Risk to Operator & Bystander

Risk to the Environment

Risk to crops

Ÿ Standard Operational practice

Ÿ Pilot training and licensing

(SOP) Ÿ Pesticide Guidance

scheme Ÿ Set safe boundary conditions (height, velocity etc.)

Ÿ Standard Operational practice

Ÿ Set boundary conditions for

(SOP) Ÿ Label Instructions Ÿ Stewardship Ÿ Pesticide emergencies and emergency response

drone use ensuring safety Ÿ Label instructions for spray applications Ÿ PPE requirements for mixing and loading

Ÿ Standard Operational practice

Ÿ Clean-up and contrainer

(SOP) Ÿ Label Instructions Ÿ Stewardship

disposal Ÿ Minimize drift by ú Set boundary conditions of (velocity, wind speed etc.) ú Nozzle type, pressure and calibration ú Mitigation measures as per label

Ÿ Avoid phytotox damage Ÿ Standard Operational Practice

Ÿ Check for phytotox risk Ÿ Mitigate drift by boundary

(SOP) Ÿ Label instructions Ÿ Stewardship

conditions and label Ÿ instructions Ÿ Select suitable application parameters (e.g. coarser nozzle selection, broadcasting granules etc.)

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Proposed Roadmap for application of agrochemicals via Drones in India I.

DAC should issue separate SOP for spraying of agrochemicals through aerial operations and through use of UAV (drone) as both are based on exclusive technologies and employed for different uses in eld or agriculture.

ii.

ICAR expert committee report on drone to be considered for framing SOP/ guidelines for “Krishi drones”.

iii.

Adopt learnings of Regulatory framework and best practices from a forward moving country like Japan.

iv.

Permission on usage of “Krishi drones” to be facilitated through digital sky platform registration in ICAR platform linked to civil aviation portal.

v.

Guidance Document: There is urgent need to develop a guidance document for regulating use of Drone for spraying CPPs by Ministry of Agriculture & Farmers Welfare (MoA&FW).

vi.

Standard Operating Procedure (SOP): Develop Best Management Practices (BMP’s) that mitigate variables impacting optimal drone pesticide application.

vii. Guidelines for Endorsement of Use of Drone in product Label and Lea et as Additional Equipment for Application of CPPs - To be established by Central Insecticides Board and Registration Committee (CIB&RC) and use of Drone as alternate equipment for spraying is to be endorsed on label and lea et of the CPPs. The data requirements for obtaining endorsement of use of drone as alternate equipment on label and lea et of an already approved crop protection product is proposed in Annexure 1. Provisional approval for use of CPPs having approved label claim on speci c crop against speci c pest/disease /weed as foliar spray using conventional spray equipment be allowed for use on same crop against same pest / disease / weeds with same active ingredient dose as foliar spray using Drone as alternate equipment for spraying until next ve years. viii. Enabling Environment: Ministry of Agriculture and Farmer’s Welfare (MoA&FW) to create favorable environment for promotion of drone use in commercial farming besides its use for research, eld trials, education, demonstration, validation or other agricultural uses by or on behalf of farmers or its use as a service by commercial/private organizations via opening of Training centers for agri-pilots, imparting knowledge of agriculture/product attributes and extending subsidies to certi ed trained pilots for purchasing/ renting of Agri-Drones etc.

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Conclusion

It would be in the interest of farmers and Agriculture in India if UAV/drone technology can be deployed for agrochemical applications. This should be supported by a robust and pragmatic science-based policy framework. We hope that the Ministry of Agriculture & Farmers Welfare (MoA&FW), CIB&RC, Ministry of Civil Aviation (MoCA) and Ministry of Home Affairs (MHA) will jointly facilitate a supportive policy framework for use of drones for application of crop protection products in India.

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List of Annexures 1.

Proposed Requirement for Approval of Drone Use as Alternate Equipment for Spraying Crop Protection Products

2.

Work ow for Using Drone for Spraying Crop Protection Products (CPPs)

3.

Recommended Standard Operating Procedure (SOP) for Drone Operation

4.

The JMAFF (Japan) Communication on UAV simpli cation 2019: talks about the registration requirements

5.

CropLife International Stewardship Guidance for Use of Unmanned Aerial Vehicles (UAVs) for Application of Crop Protection Products

6.

CropLife India’s Feedback/Observations/Perspective on SOP for Aerial Spraying by Aircraft /helicopter/drones and Report of the Sub-committee to frame the guidelines for use of drones for pesticide applications in Locust control, Plant protection and Public health.

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Annexure-1 Proposed Requirement for Approval of Drone Use as Alternate Equipment for Spraying Crop Protection Products Pre-requirement: 1. Formulation Suitability: Stability of formulations after diluting in required quantity of water i.e. 15 to 50 lit. Water / ha (which is required for application by Drone). There should not be foaming, sedimentation, etc. (Note: Generally, most high-quality formulations/Products are suitable for Drone including SC, WDG, OD, EC types.) Requirements: A] Product is Already Approved for Use with Conventional Spray Equipment: For Crop Protection Products which have approved label claims for use on speci c crops against speci c pests / diseases / weeds when foliarly applied using conventional spray equipment’s e.g. back pack sprayer, etc. and submitting application for obtaining label claims on same crops against same pests / diseases / weeds with same approved active ingredient dose as foliar spray using Drone as alternate equipment for spraying.

Studies

Insecticides

Fungicides

Herbicides

Plant Growth Regulators

Bio-effectiveness

NR

NR

NR

NR

*Phytotoxicity (crop safety)

1-2 L 1 S

1-2 L 1 S

1-2 L 1 S

1L1S

Effect on parasites & predators

NR

NR

NR

NR

Effect on Succeeding Crop

NR

NR

NR

NR

Persistence in Plant

NR

NR

NR

NR

Residue in Plant

NR

NR

NR

NR

Residue in Soil

NR

NR

NR

NR

L – Location

S – Season

NR – Not Required

Minimum plot size (International Standard): 320 sq. m (20 m x 16 m) *J-MAF permits a simple potted plant phyto-toxicity test

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B] For New Products Approval (for combined approval with Knapsack and Drone application): Studies

Insecticides

Fungicides

Herbicides

Plant Growth Regulators

Bio-effectiveness

3L2S

3L2S

3L2S

3L2S

Phyto toxicity (crop safety)*

3L2S

3L2S

3L2S

3L2S

Effect on parasites & predators

3L2S

NR

NR

NR

Effect on Succeeding Crop

NR

NR

3L2S

NR

Persistence in Plant

NR

NR

NR

NR

Residue in Plant

4L1S

4L1S

3L2S

4L1S

Harvest time Residue in Soil

4L1S

4L1S

3L2S

4L1S

L – Location

S – Season

NR – Not Required

All studies with back pack sprayer *Additional study with Drone (1L1S if label claim is for both knapsack and drone spray, keeping rest of the studies data using conventional spraying only) Minimum plot size (International Standard): 320 sq. m (20 m x 16 m)

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Annexure-2 Work Flow for Using Drone for Spraying Crop Protection Products (CPPs)

Drone Owner or Service Provider

Obtain UIN No. UAOP No

CPP Manufacturer

Digital Sky Platform (Directorate General of Civil Aviation)

New Product Application or Endorsement on Label and Lea et of approved product to Use Drone as Alternate Equipment for Spraying CPPs

Central Insecticides Board and Registration Committee

Obtain Permission in Digital Sky Platform to Fly Drone

CIB&RC Approved CPP Drone

Spraying of CPP on Crops Using Drone UAOP: Unmanned Aircraft Operator Permit UIN: Unique Identi cation Number

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Annexure 3 Recommended Standard Operating Procedure (SOP) for Drone Operation Pre-application: 1.

Con rm not to y in the drone-forbidden area (airport or electronic station).

2.

Understand the local aviation laws and regulations where they operate.

3.

Ensure the operators are trained on both drone operation and safe use pesticide. Use adjuvant against evaporation and drift ability (methylated seed vegetable oil – MSO or other oils).

4.

No alcoholic drinks within 8 hours preceding operation.

5.

Calibrate drone spray system to ensure nozzle output and accurate application of labeled rates.

6.

Check drone in good condition, no leak in the spraying system.

7.

Con rm place for takeoff and landing, tank mix operations.

8.

Check and mark the obstacles (walls, trees) around the eld for safe operation.

9.

Set up at least buffer zone (as speci ed in SOP) between drone treatment and the non-target crop.

- Con rm water sources - Do not spray pesticides near water sources (less than 100 m) to avoid polluting water sources. During Application: 1.

Read labels carefully to understand safety guidance.

2.

Wear Personal Protect Equipment (PPE).

3.

Do not eat, drink or smoke while spraying.

4.

Con rm the ying route was reasonable to minimize turn around.

5.

Operation team shall always stay at the downwind end of the eld and backlight direction.

6.

To spray with pure water rst to test operation for at least 5 min.

7.

Two step dilutions to fully dissolve the pesticide.

8.

Adopt proper pressure for optimized droplet spectrum (approx 200μm).

9.

Check weather conditions: a.

Wind speed less than 3m/s,

b. Temperature lower than 35 degrees, c.

Humidity above 50%).

wind speed

temperature

humidity

<3m/s

<35o(

> 50%

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- Flying height: 3m above target crop. 11. Water volume: normally 15-50 Lit./ha. 12. Flying speed: 3 - 6 m/s. 13. Avoid having to walk through crop which has been contaminated by drifting spray. 14. Do not spray during active bee foraging period of the day. Avoid spray drift to owering nectar crop. 15. When spraying pesticides that are toxic to non-target organisms such as sh, birds and silkworm, strictly abide by the product label requirements and take effective measures to avoid risks. 16. Use anti-drift nozzle to decrease drift to human and environment (Air-mix, 110 01, 110 075).

Post Application: 1.

Timely evacuation and transfer to fresh air.

2.

Triple rinse of empty container is mandatory.

3.

Ensure waste generated is kept to a minimum.

4.

The disposal of waste must conform to the local laws.

5.

Never burn or bury hazardous waste.

6.

Never leave empty containers in the eld. Send triple rinsed empty containers to the nearest approved collection site.

7.

Set up warning signs in the spray area for reminding people.

8.

Take a shower and put on clean clothes.

9.

To prevent leakage of plant protection products in the process of transport and waiting to use.

- Securely stored plant protection products away from unauthorized people, animals and food when transporting and storing PPP. Safely dispose all spills immediately. Different Standards in Terms of; Prerequisites to Use Drones, Minimum Area, Climatic Conditions viz Temp., Wind Speed, Height of Application, Droplet Size, etc. to be followed in use of Drones to offset Drift and Air pollution. Application / spraying of Crop Protection Products (CPPs) either using conventional spray equipment’s or using drone, requires to follow stewardship measures. For use of Drone for spraying CPPs following key stewardship measures to be followed for excellent performance and safety.

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Flying Height

Travelling / Flying Speed

Spray Width

Water Volume /Ha

Nozzle Type

Drone

1.5 – 3 m above crop

3 – 6 m/s 10 minutes per acre

3 – 5 m (depends on rotor number and boom length)

15 – 50 Liters

Flat fan or controlled droplet applicator (CDA) nozzle with approx 200 µm Droplet size

Knapsack

0.6 – 1.0 m from the top and sides

1-2 m/s One hectare/ 8 hours

Single nozzle

360 – 500 Liter

Standard Hollow Cone / Flat Fan Nozzle

Tractor mounted boom sprayer

0.45 – 0.9 m above the crop

3 kms/hour Boom length 500 – 1000 Liter Standard One Hectares / approx. 11 meters Hollow Cone / Hour (depend on Flat Fan Nozzle nozzle number and boom length and position)

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Annexure 4 The JMAFF (Japan) Communication on UAV simpli cation 2019 2018 MAFF/FSCAB Noti cation No 5541 22 February 2019 To MAFF Food Safety and Consumer Affairs Bureau Plant Products Safety Division Director

HANDLING OF STUDIES WHICH REQUIRE DECLARATION AND SUBMISSION OF A METHOD FOR USING AN AGRICULTURAL CHEMICAL In recent years, progress in the active use of drones for spraying agrochemicals, in order to save energy and increase efficiency, has led to studies regarding application of the Agricultural Chemicals Regulation Law (Law No. 82 of 1948) in relation to spraying of agricultural chemicals by using drones, etc., and/or the content of the test results which need to be submitted in relation to such spraying of agrochemicals. Here we wish to clarify our interpretation of the Agricultural Chemicals Regulation Law in relation to the declaration of methods for using agricultural chemicals and spraying equipment, as in 1 below, and also inform you of reassessment of the results of studies required in relation to spraying of agrochemical, using drones, etc., as in 2 below. Declarations of Understanding 1. According to the Agricultural Chemicals Regulation Law, in declaring “spraying of stems and leaves of weeds” and “comprehensive spraying of soil”, etc., as methods for employing an agrochemical, the person employing the agricultural chemical is free to judge the spraying equipment to be employed for spraying the agricultural chemical, without any restriction as to the choice of the spraying equipment, including use of a drone. 2. The “Data Requirements for Registration of Agricultural Chemical” (2000 MAFF/APB Noti cation No. 8147 (12-Nousan-8147) by the Director, Agricultural Production Bureau, Ministry of Agriculture, Forestry and Fisheries dated 24 November 2000) has been revised in “Partial Revision of “Data Requirements for Registration of Agricultural Chemical” (MAFF/FSCAB Noti cation No 5464 (Director General, MAFF Food Safety and Consumer Affairs Bureau) dated 22 February 2019), (Appendix) According to this revision, when applying for modi cation of the registration of an already registered agricultural chemical for use at a high concentration diluted several times in order to spray by using a drone, etc., (1) If the amount of the active ingredient deposited per unit surface area is within the range

initially applied for, there is no need to submit crop residue tests in addition to those at the time of the initial application for registration. (2) When a study on phytotoxicity can con rm the existence or otherwise of phytotoxicity, there is no restriction as to eld studies.

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Table comparing data requirements for registration of agricultural chemicals (2000 MAFF/APB Noti cation No. 8147 (12-Nousan-8147) by the Director-General, Agricultural Production Bureau, Ministry of Agriculture, Forestry and Fisheries dated 24 November 2000) before and after the proposed partial revision (abridged) (Underlining shows the revised portions)

After revision

Current

(Appendix) 2 Regarding conditions relevant to preparation of study results The test results cited in Section I must be obtained by implementing the tests cited in the “Test items” column in Appendix Table 1, on the basis of the conditions cited in the “Conditions Necessary for Implementing Studies / Tests” column in the same table. The test methods are to be those stipulated in the appendix entitled “Guidelines on Preparation of Test Results Submitted When Applying for Registration Of Agricultural Chemicals”; but among results of studies relating to calculating predicted environmental concentrations“Monitoring of concentrations of the agricultural chemical in rivers” should only be applied in the case of agricultural chemicals which are currently receiving registration.

(Appendix) 2 Regarding conditions relevant to preparation of study results The test results cited in Section I must be obtained by implementing the tests cited in the “Test items” column in Appendix Table 1, on the basis of the conditions cited in the “Conditions Necessary for Implementing Test” column in the same table. The test methods are to be those stipulated in the appendix entitled “Guidelines on Preparation of Test Results Submitted When Applying for Registration Of Agricultural Chemicals”; but among results of studies relating to calculating predicted environmental concentrations“Monitoring of concentrations of the agricultural chemical in rivers” should only be applied in the case of agricultural chemicals which are currently receiving registration.

(Appendix Table 1)

(Appendix Table 1)

Conditions Necessary for Implementing Studies / Tests Study//Test Test Study Test items results results

Type of No. of trials/type of test crops or test test substance animals, etc.

Implemen tation method number (see annex)

Implemen tation method number (see annex)

(omitted) (omitted) (omitted)

(omitted)

(omitted)

(omitted)

(omitted)

(omitted)

Study /test facilities conforming to GLP standards for agricultural chemicals. However, for a crop whose production volume is low, GLP compliance is not required. Field trials shall be conducted according to the following standards. (1)-(6) (omitted) (deleted)

3-1-1

(omitted) (omitted) (omitted)

(omitted)

(omitted)

(omitted)

Results of studies / tests of residues in crops

Crop residue studies

Conditions Necessary for Implementing Studies / Tests Study//Test Test Study Test items results results

Type of No. of trials/type of test crops or test test substance animals, etc.

Implemen tation method number (see annex)

Implemen tation method number (see annex)

(omitted) (omitted) (omitted)

(omitted)

(omitted)

(omitted)

(omitted)

(omitted)

3-1-1

(omitted) (omitted) (omitted)

(omitted)

Study / test facilities conforming to GLP standards for agricultural chemicals. However, for a crop whose production volume is low, GLP compliance is not required. Field trials shall be conducted according to the following standards. (1)-(6) (omitted) (7) When aerial spraying or unmanned helicopter spraying is added as a method of using an agricultural chemical registered for ground application, the number of test examples of this aerial spraying or unmanned helicopter spraying shall be at least half of the necessary examples (2 or more, when the number of examples necessary is 3). (omitted)

Results of studies / tests of residues in crops

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Crop residue studies

(omitted)

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Current

After revision

(Annex) “Guidelines for Preparation of Study Results Submitted When Applying for Registration of Agricultural Chemicals”

(Annex) “Guidelines for Preparation of Study Results Submitted When Applying for Registration of Agricultural Chemicals”

Efficacy study for target pests Efficacy and phytotoxicity studies (1-1-1)

Efficacy study for target pests Efficacy and phytotoxicity studies (1-1-1)

1. • 2. (omitted) 3. Study method (1) A study is carried out in the eld (or in such facilities as are applicable), with plots treated with the agricultural chemical and untreated plots and as a rule plots treated with a control chemical, of an adequate area for achieving the purpose of the study. Treatment with the agricultural chemical in chemically treated plots is with the method and dosage (concentration) relevant to the application for registration.

1. • 2. (omitted) 3. Study method (1) A study is carried out in the eld (or in such facilitiesas are applicable). However, for phytotoxicity studies in the case of an already registered agricultural chemical, when the concentration used or the quantity used (quantity of active ingredient delivered) is increased, if a study can

con rm the existence or otherwise of phytotoxicity, there is no restriction as to eld studies. In addition, in order to achieve the purpose of the study there shall be plots treated with the agricultural chemical and untreated plots and as a rule plots treated with a control chemical, of an adequate area. Treatment with the agricultural chemical in the agricultural chemical treatment plots is with the method and at the quantity (concentration) used according to the request for registration.

(2) • (3) (omitted) 4. (omitted)

(2) • (3) (omitted) 4. (omitted)

Supplemental (22 February 2019) The stipulations as revised according to this noti cation shall apply to the results of studies submitted in support of applications for registration of an agricultural chemical carried out from 22 February 2019 onwards.

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Annexure 5 CropLife International Stewardship Guidance for Use of Unmanned Aerial Vehicles (UAVs) for Application of Crop Protection Products •

Know and comply with the relevant laws.

•

The Drone Operator should be trained both in Responsible Use of Agrochemicals & Drone Operations.

•

Spray Equipment – Before spraying, ush water through the systems to remove residual air bubbles and check if any leaks can be identi ed from damaged connections, hoses, etc.

•

Documentation – Check necessary documentation including UAV registration and license, pest control and/or chemical handling license. If a farmer hires a service to apply pesticides by UAV, they should check that the company being contracted has the appropriate documentation.

•

UAV t for ight – Carefully go through the manufacturer's pre- ight checklist and check every part for signs of damage or obstruction. Ensure that batteries and reserves are adequately charged, and that battery charging equipment is available if required. Check functioning, controller, etc. If the UAV is hybrid or gas powered, ensure that there is sufficient fuel in a container safe to store and transport.

•

Firmware – According to the manufacturer's instructions, check the UAV rmware and ensure it is up to date. Ensure that your UAV is always calibrated for connectivity, navigation, and behaviour. Check pre- ight settings e.g. compass, LED status, satellite locks, gimbal level, and ight controls.

•

Calibrate Sprayer – Good UAVs will be tted with an automatic internal-pump calibration system. Test water should be added according to the manufacturer's instruction, the amount and nozzle types entered into the system and the UAV set to run the calibration system on the ground. This should be repeated for a second pump if it is present. Placing graduated measuring cups under the nozzles will allow the comparative outputs to be judged. Any irregularities could mean that nozzles are worn or damaged and need to be replaced. If this is not the case, then there is an imbalance in the system that may require further investigation according to manufacturer's recommendations.

•

Flying conditions and itinerary – Check the weather and temperature. Understand the area to be treated, as well as the surrounding area, including water bodies, other cropping areas, residential areas, and beehives.

•

Crop and pest targets – The identity of the crop, growth stage and canopy height should be con rmed along with the location of pests and diseases. It is important to check that the nozzles, pressure settings, and formulation are appropriate for delivering the right sized droplets for the job. Only pesticides appropriately registered for use against the target from UAV application should be used. Understand the pesticidal attributes of the product and follow label directions-for-use to optimize crop protection. ü Always Use Personal Protective Equipment, while handling Agro-chemicals. ü Save yourself from fake products by insisting on Receipt of Purchase.

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Annexure 6 CropLife India's Feedback/Observations/Perspective on SOP for Aerial Spraying by Aircraft / helicopter/drones and Report of the Sub-committee to frame the guidelines for use of drones for pesticide applications in Locust control, Plant protection and Public health.

CropLife India's Observations/ Comments/Perspectives

Report/ Observations of CIB Sub-committee

Provisions under the Insecticides Act/Rules

- The Board after deliberation approved the SubCommittee Report to frame guidelines for use of drones for insecticide (pesticides) applications in locust control, plant protection and public health…..and Standard Operating Procedure (SOP) for aerial spraying of insecticides prepared by the Directorate of Plant Protection Quarantine and Storage, Department of Agriculture, Cooperation and Farmers Welfare, which also include use of drone, as per Annexure XIII.
- One of the functions of the board is to specify the uses of the classi cation of insecticides on the basis of their toxicity as well as their being suitable for aerial application (Rule 3(b)).

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As per the provisions of the Insecticides Act and Rules, Label/lea ets are approved by the Registration Committee (RC) under the Act. These label/lea ets besides other information also provide information on the type and stage of crop, pest-diseases to be controlled, equipment to be used for application of pesticide, dilution, rate of spray, conditions of spray etc. based on the data submitted by the applicant to the Registration committee. Hence, before permitting the application of pesticide through Drones, data generated as per guidelines of the RC (yet to be framed for drones) need to be evaluated for ensuring the efficacy of the product and its safety to human and environment.

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The SOP of Aircraft and Helicopter should not be applied to Drones (UAS) for application of pesticides for locust control as Drones are based on exclusive technologies and employed for different uses in agriculture ecosystem.

Ÿ

It would be appropriate to develop a separate SOP on use of UAS (Drone) for application of pesticides in locust control, plant protection and public health.

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The MoCA has also released separate draft UAS Rules, 2020 for regulating Drones to separate it from Aircraft Rules, 1937.

Ÿ

The height of spray with Drone and Aircraft/Helicopter are not comparable and consequentially spraying through drones (1-3 m height) offers a much safer and precise application of pesticides.

Ÿ

Pesticide application via Drone should be considered as alternate equipment for application of pesticides and there should not be undue apprehension about their safety and success under Indian agricultural conditions.

Ÿ

Integration of Drone is not going to impact our approved product usages viz. stage of crop, pest-diseases to be controlled, rate of application of pesticide, conditions of spray etc., therefore, generation of additional data as insisted by CIB & RC is not going to give further bene t, rather it will delay the introduction of Drone technology.

Ÿ

Drone technology can ensure proper coverage of the foliage, it can operate over sodden elds and tall crops where no machine could normally move, go quickly to exact locations to treat target areas precisely, as well as be pre-programmed to navigate their own way around.

Ÿ

Integration of Drone should be considered as endorsement of alternate equipment for application /spraying of pesticides which broaden the scope for farmers to use advance and user-friendly technology for our own farm treatment. However, if insisted or required, the crop injury / phyto-toxicity studies from one or two location may be asked to make sure the crop safety.

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In future and under COVID situation, this technology

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CropLife India’s Observations/ Comments/Perspectives

Report/ Observations of CIB Sub-committee

should be considered as boon because labour crisis in the eld of agriculture is becoming one of the biggest challenges, as younger workers leave to seek more pro table employment in cities, an aging workforce is left in rural areas. In India and many developed countries, it is increasingly becoming an issue leading to an increased demand for labor saving, efficient technologies. Spraying from Drone offers substantial labor-saving opportunities.

Development of Guidelines for Drone use in India Ÿ

A committee was constituted by Department of Agriculture, Cooperation & Farmers Welfare (M& T Division), Ministry of Agriculture & Farmers Welfare, Government of I ndia in May 2019 under the chairmanship of Dr. K. Alagusundaram, DDG (Agri. Eng.), ICAR

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Committee under chairmanship of Dr. Alagusundaram worked extensively on use of Drone in agriculture for application of pesticides. They involved & considered views of stakeholders ranging from Drone manufacturers & service provider to pesticide industry and farmers.

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The terms of reference of the Committee are to develop guidelines for operation of drones in application of spraying of pesticides, growth hormones, fertilizers in different crops at different stages.

Ÿ

The report / recommendations of Dr. Alagusundaram Committee jointly discussed in meeting held on 20th February 2020 (also attended by representatives of CIB&RC) may kindly be considered in holistic manner as it incorporate inputs from multiple stakeholders.

Ÿ

No further guidelines of M/o Civil Aviation exist w.r.t. clause 12.18 which refers to special clearance for discharging or dropping the substances.

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Ministry of Civil Aviation (MoCA) published draft UAS Rules, 2020 through Gazette Noti cation dated 2nd June 2020.

Ÿ

Clari cation is required from the M/o Civil Aviation w.r.t. clause 12.19 in their guidelines which prohibits the transport of hazardous material in RPA.

Ÿ

As per rule 36 and 38 of this draft Rules, DGCA shall specify the payload to be carried by Drones and dropping of articles from Drone, respectively.

Guidelines /Scenario in other Countries Ÿ

EU: Aerial application including use of drones is completely banned.

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Switzerland: pilots must receive authorisation, meet comprehensive safety regulations and keep drift below a de ned threshold.

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USA: Use of drones is permitted provided pilots comply with strict Federal Aviation Operational Rules as well as requirement of aerial application.

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The European Union, known for their restriction of manned aerial application, is now considering the use of drone pesticide application. EU is developing guidance for use of Drones for spraying pesticides for areas inaccessible to vehicles and where manual spraying is difficult e.g. Grapes orchards on sloppy hills. Recently, Switzerland has approved use of Drone for spraying on agriculture crops.

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CropLife India’s Observations/ Comments/Perspectives

Report/ Observations of CIB Sub-committee Ÿ

Canada: Drone use for pesticide application is illegal.

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As most of the agriculture systems in India belongs small and marginal sector, it would not be the best option for small and marginal farmers to apply pesticides by drone technology.

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Given the warm climate with wide range of variability it would be difficult to mitigate exposures and drift risk caused by pesticides.

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Usually farmers have their residential huts/houses also in the same premises at a little distance and the livestocks are also kept in the same farm making it further difficult to avoid the exposure.

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When land holdings are very big, the application of pesticides through Aircraft or Helicopter is more economical than Drone. That is why acceptance of Drone for application of pesticides is more in Asian countries where land holdings are comparatively smaller than North America and Europe.

Ÿ

Drone Application Technology is also suitable for spraying pesticides in small and marginal agriculture farms including areas where manual spray operation is difficult as it offer following advantages

The technology is expensive and its affordability by small and marginal farmers is to be seen.

There are some sectors where the use of this modern technology may deliver bene ts like Ÿ

for control of big locust swarms;

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in some public health situations to control vectors of diseases; and

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for plant protection where corporate plantation is practiced like tea estates.

Ÿ

Precision in spraying

Ÿ

Less time required to spray unit area

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Minimal or no operator exposure

Ÿ

Low water volume

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The use of Drone for pesticide application is suitable for spraying in small land holdings as the spray area can be de ned with precision (Geo-tag of the spray area).

Ÿ

The Drone Technology provides provision to avoid obstacles in the ying path which prevent any accidents and exposure as well.

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Unlike backpack sprayers, farmers are not required to own the Drones & they can avail spray services from Drone service provider.

Ÿ

In addition to use of Drone in locust control, public health and plant protection where corporate plantation is practices like tea estates, Drone Application Technology is also suitable for spraying pesticides in small and marginal agriculture farms including areas where manual spray operation is difficult. Ÿ

Advantages of Drone Spraying

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Precision in spraying

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Less time required to spray unit area

Ÿ

Minimal or no operator exposure

Ÿ

Low water volume

Hence, drones are also useful in small and marginal agriculture farm sector for spraying pesticides.

Recommendations by Sub-committee Ÿ

- A clari cation is required from the M/o Civil Aviation w.r.t. clause 12.19 in their guidelines on Drones which prohibits the transport of hazardous material in RPA. As pesticides are hazardous substances, hence the clari cation is required.

Clause 12.18 and 12.19 are related to Civil Aviation Requirements 1.0 published by DGCA under provision of the Aircraft Rules, 1937, which became effective in India from 1st December 2018. However, UAS Rules, 2020 (draft) have been published by MoCA through draft Gazette Noti cation dated 02.06.2020. As per these draft UAS Rules, DGCA shall specify the payload and dropping of articles as per rules 36 and 38, respectively.

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CropLife India’s Observations/ Comments/Perspectives

Report/ Observations of CIB Sub-committee 2. Applicant seeking permission for spraying of pesticide by RPA should obtain special clearance from M/o Civil Aviation for discharging or dropping the substances as per clause 12.18 of their guidelines. 3. Applicant should comply and follow the guidelines of the Civil Aviation Ministry for use of RPA /drones and should have permission for undertaking the pesticide application operation.

Permission for Drone operations including payload and dropping of articles need to be taken by the applicant and comply with Drone regulations issued by MoCA. However, permission for undertaking pesticide application should be given by CIB&RC by way of label claim approval for products which are already approved for use with knapsack sprayer and have already undergone adequate risk assessment for their safety and efficacy. Suitable provisions needs to be made in Digital Sky Platform.

The application of pesticides through drones is permitted only for the following situations: ii) Use of Drone in Public Health Ÿ

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To control vectors of the diseases by M/o Health & Family Welfare under National Vector Disease Control Program. In addition to compliance of requirements of the Civil Aviation Rules and other provisions under the Insecticides Act & Rules and other safety precautions, detail guidelines/SOP may be formulated by the M/o Health & Family Welfare The proposal received from the Government authorities (Central or State Government/ Municipal Corporation) which comply to SOP shall be placed before the Central Insecticides Board for grant of permission.

The proposals received by the IPM Division, Directorate of PPQ&S for granting permission for use of drone in agriculture/ horticulture will be examined by a Technical Committee (comprising of Plant Protection Experts& Medical Toxicologist) constituted by the Plant Protection Adviser prior permitting use of drone in agriculture/ horticulture. Plant Protection Adviser will submit details of such approvals in the subsequent meeting of the Board.

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Guidelines/SOP may be formulated by the M/o Health & Family Welfare for use of Drone in Vector control.

•

There are provisions like, No Permission No Take-off (NPNT) available in Digital Sky Platform.

•

Drone application technology should be treated as alternate equipment and to be endorsed on the product label as alternate equipment only. The registered products have already undergone adequate risk assessment during the registration.

•

Since, spraying through Drone is not comparable with aerial application by using Aircraft and Helicopter (separate draft UAS Rules, 2020 issued by Ministry of Civil Aviation), the approval for use of Drone for spraying as alternate equipment in product label and lea et may be granted by CIB&RC.

Spraying with Drone is not comparable with aerial spray done through Aircraft and helicopter. Hence,

The proposals complying to above requirements for application of pesticides through drones will be placed before the Central Insecticides Board for consideration and grant of permission for application of pesticides

through drones for the speci c purpose and for the speci ed period. Thereafter, renewal of permission will be required.

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The permission for use of Drone for spraying of pesticides may be given by CIB&RC by way of endorsement on label lea et as alternate equipment for spraying.

•

Once Permission from CIB to use drone as an alternate equipment for spraying the pesticides is obtained, the renewal of such permission should not be required separately.

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CropLife India's Observations/ Comments/Perspectives

Report/ Observations of CIB Sub-committee Decision by CIB •

The Board after deliberation approved: Ø

The Sub-Committee Report to frame guidelines for use of drones for insecticide (pesticides) applications in locust control, plant protection and public health.

Ø

Standard Operating Procedure (SOP) for aerial spraying of insec ticides prepared by the Directorate of Plant Protection Quarantine and Storage, Department of Agriculture, Cooperation and Farmers Welfare, which also include use of drone.

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We request that Industry / stakeholders views/comments on the Sub-committee report may kindly to be sought and considered before approval by CIB.

About FICCI Committee on Drones FICCI has many specialised committees where key concerns of the industry are debated and discussed with the speci c aim of presenting the recommendations to the Government for favourable decisions. FICCI has identi ed drones as one of the priority areas. FICCI Committee on drones (UAV / UAS / RPAS) has been working on the policy advocacy and the regulatory framework to facilitate the growth of ecosystem for drones in the country. This committee has been advocating for the holistic and responsible use of Drone technology across government agencies, agriculture, and enterprises. Some of the focus areas of the Committee are • Regulatory Evolution • Industry licensing regime • Operations regulations • Import/export-regulation • Counter drone technologies • UAV exports from industry • Demand analysis for drones • User sensitization / Formal education Snapshot of the various FICCI studies on Drones:

FICCI Recommendations on the Draft UAS Rules, 2020

Covid 19 Scenarios–Emerging Role of Drones, 2020

FICCI EY Countering Rogue Drones, 2019

Make in India for Unmanned Aircraft Systems (UAS), 2018

FICCI Survey based Recommendations on the draft DGCA circular on Requirements for Operation of RPAS, 2017

FICCI submission on DGCA's draft circular on Guidelines for obtaining UIN and Operation of Civil Unmanned Aerial Systems (UAS), 2016

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About CropLife India CropLife India is committed to advancing sustainable agriculture and it is an association of 15 R & D driven member companies in crop protection. We jointly represent ~ 70% of the market and are responsible for 95% of the molecules introduced in the country. Our member companies have annual global R

& D spend of 6 billion USD and are rmly committed to engaging with the farming community to enable Safe, Secure Food Supply.

Our Members

SWAL

Our Associate Members

About FICCI Established in 1927, FICCI is the largest and oldest apex business organisation in India. Its history is closely interwoven with India's struggle for independence, its industrialization, and its emergence as one of the most rapidly growing global economies. A non - government, not - for - pro t organisation, FICCI is the voice of India's business and industry. From in uencing policy to encouraging debate, engaging with policy makers and civil society, FICCI articulates the views and concerns of industry. It serves its members from the Indian private and public corporate sectors and multinational companies, drawing its strength from diverse regional chambers of commerce and industry across states, reaching out to over 2,50,000 companies. FICCI provides a platform for networking and consensus building within and across sectors and is the rst port of call for Indian industry, policy makers and the international business community.

FICCI

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Source: `EMP.pdf` · Google Drive file id `1SeGKxyeEiRjVPgpnOzsZqH7PXDClB7z5` · folder “8. Agricultural University Research”

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College of Food, Agricultural, and Environmental Sciences

FABE-540

Drones for Spraying Pesticides— Opportunities and Challenges Erdal Ozkan; Professor and Extension State Specialist—Pesticide Application Technology; Department of Food, Agricultural and Biological Engineering; The Ohio State University Traditionally, aerial spraying of pesticides has been done using conventional fixed-wing aircraft or helicopters with a pilot onboard. However, this is changing. Small, remotely piloted aircraft are being used to apply pesticides around the world, especially in Southeast Asia. For example, about 30% of all agricultural spraying in South Korea, and about 40% of Japan’s rice crop, is sprayed using drones. In contrast, drone spraying is in its infancy in the United States, but interest in this technology from pesticide applicators is steadily increasing. A variety of names and the acronyms are associated with remotely piloted aircraft:

- unmanned aerial vehicle (UAV)
- unmanned aerial system (UAS)
- small unmanned aerial system (SUAS)
- remotely piloted vehicle (RPV)
- remotely piloted aircraft (RPA)
- remotely operated aircraft (ROA)
- remotely piloted aerial application system (RPAAS) Although UAV and UAS are the most commonly used names given to this kind of technology, the name used most commonly by the general public is “drone,” which is used throughout this document. This publication highlights drone sprayer specifications, why they may be the choice for aerial spraying, and the challenges that reduce their usage by pesticide applicators. Drones entered the agriculture scene initially for non-spraying applications, such as crop and fieldcondition data collection to increase profitability in crop production. Drones capture a number of important data points:

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- soil characteristics (type, moisture content, and nutrient content)
- location of drainage tiles
- crop nutrient stress level
- crop emergence or stand count
- weed species and infestation level
- detection of insects and diseases Drones successfully and effectively monitor plant growth by collecting and delivering real-time data from the moment of plant emergence to harvest. With the help of fast and accurate GPS (Global Positioning System) or GNSS (Global Navigation Satellite System) technology, a high-resolution camera, and variable flying speeds and altitudes, drones can provide a wealth of information on the condition of every half square inch of crop or soil. Using drones for spraying pesticides is attractive mainly for four reasons: 1. The topography or soil conditions do not allow the use of traditional ground sprayers or conventional agricultural aircraft. 2. When airplanes and helicopters are not available or are too expensive to use. 3. Drones more efficiently spray small, irregularshaped fields.

ohioline.osu.edu/factsheet/fabe-540

- Drones significantly reduce the risk of applicators being contaminated by the pesticides, especially those using backpack sprayers. There are also emerging problems, such as tar spot on corn, which may increase the need for aerial pesticide application by drones.

Drone Sprayer Performance Although they are small, drone sprayers have nearly all the components of large ground sprayers and conventional aerial sprayers:

- tank
- pump
- hoses
- filters
- nozzles
- flow meter All drone sprayers are also equipped with a GNSS receiver and multiple sensors for collision avoidance. All drones also have wireless remote control. Each component of the drone plays a critical role in achieving maximum sprayer performance. Spraying with a drone is not new. First used in Japan in 1997, the Yamaha RMax drone looks like a small helicopter (Figure 1). It has a single rotor with a diameter of about 10 feet, weighs 207 pounds, and has over 4 gallons of spray tank capacity. With a full tank and spraying at 1 gallon per minute, the tank is likely to be empty in about 4 minutes. It is gasoline powered, can run for 1 hour before refueling, can be retrofitted with three or four nozzles, and was FAA-approved for use in California in 2015. This aircraft has a terrain sensor and can be operated manually or on autopilot. The 2 | Ohioline.osu.edu

yamahaprecisionagriculture.com

Figure 1. Yamaha RMax single-rotor drone.

manufacturer does not sell the aircraft, rather they service it and provide a trained team (usually two to three people) to operate the aircraft. A rapid proliferation of lighter, easy-to-operate drones for spraying pesticides is currently underway. They are lightweight but powerful enough to lift a 10–15-gallon tank. Most commercial spray drones today are the multi-rotor type shown in Figures 2–4 and 6–8 on the following pages. The drones' propellers create turbulence in the canopy, which significantly improves droplet penetration into lower parts

of the canopy compared to traditional ground sprayers that are not air-assisted. Multi-rotor drones have similar components but can differ in many ways:

- number of rotors
- rotor positions
- nozzle locations and configurations
- type and number of nozzles
- distance between nozzles
- vertical distance between the rotors and the nozzles under them

Ken Giles, UC Davis

For example, most drones have nozzles located on the end of hoses descending a few inches below the rotors (Figure 2). A smaller percentage of drones have nozzles mounted on a boom (Figures 3 and 4). One drone type, shown in Figure 5, has four rotor arms with two rotors on each arm powering a pair of impellers that are stacked one on top of the other. This dual rotor configuration provides a more powerful lifting capacity and better flight dynamics. Drones with a boom, and especially those with booms extending beyond the rotors as shown in Figure 4, usually are not preferred. These drones are likely to become obsolete because of relatively poor spray coverage compared to the boomless spray drones as shown in Figure 2.

Drones for Spraying Pesticides—Opportunities and Challenges

GPS

NOZZLES

TANK

Erdal Ozkan, The Ohio State University

Figure 3. Spray drone with a boom.

Erdal Ozkan, The Ohio State University

Figure 2. Spray drone with no boom.

They also have a higher drift potential influenced by vortices that appear near both ends of the boom as shown in Figure 6. Having a larger number of nozzles on the boom, and having a boom that does not extend too far outside the rotors may help avoid this problem, resulting in much better penetration of spray droplets into the target plant canopy and a better coverage of the target surface with droplets. The newest design for discharging spray from drones uses rotary atomizers positioned under large propellers (Figures 7a, and 7b, next page). These atomizers are sometimes referred to as controlled droplet atomizers (CDAs). The spray droplets are produced by the rotational speed of a cup, which allows the spray mixture to be emitted using very low pressure. This design produces relatively uniform droplets as opposed to the wide range of droplet sizes produced by conventional flat-fan nozzles. Some of the more recent and relatively more expensive drone models, like the one shown in Figure 8 (next page), are equipped with a larger, 10-gallon spray

tank with multiple nozzles per nozzle outlet, larger batteries that can provide power for heavier payloads, and wireless connectivity. Unfortunately, as demonstrated by the small sample of drone sprayers shown in this fact sheet, no standards exist for the most optimum spray drone design, especially related to the location and configuration of nozzles on the drone. As a result, drone purchasers are faced with a number of unanswered questions:

- Is it better to have a drone with a boom under the rotors, or is it

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Figure 4. A spray drone with a boom extending too far away from the rotors is not preferred because of poor spray deposition and coverage, and high drift potential.

DJI.com

Figure 5. Spray drone with two rotors at each arm, powering a pair of impellers one above the other one.

Adobe Stock

Figure 6. Drift potential from drones with a boom may be excessive depending on the size of the boom and the type and size of nozzle used.

Drones for Spraying Pesticides—Opportunities and Challenges

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DJI.com

Figure 7a. Spray pattern produced by the dual spray atomizer.

Erdal Ozkan, The Ohio State University

Figure 8. A sprayer drone with a 10-gallon tank and multiple nozzles under each rotor.

deposition and spray coverage on the target. Dr. Steve Li, Auburn University

Figure 7b. Close up of a Controlled Droplet Atomizer (CDA).

better to have nozzles directly under each rotor?

- If a boom is better, what should the boom width and its distance from the rotors be?
- If having nozzles at the end of a drop-down hose under each rotor is a better option, what should be the length of the hose?
- What are the best type of nozzles for different spraying jobs?
- Is there an optimum distance between nozzles?
- Should there be one nozzle at the end of the drop hose, or multiple nozzles as shown in Figure 8? So far, drone configurations do not have the standardization seen in conventional, piloted aerial aircraft. This is because no studies have been conducted, or models developed, to determine the most optimum drone design parameters to minimize drift and to maximize 4 | Ohioline.osu.edu

Operating Characteristics of Multi-rotor Spray Drones The application rate of spray drones in row crops is usually 1.5 to 2 gallons per acre. The rate depends on many factors, but is mainly a function of the spray tank capacity, flying speed, spray swath width, number of nozzles or rotary atomizers on the drone, and the flow rate (volume sprayed per minute). For example, a 5-gallon tank may take 2–3 minutes to empty. Some drones have a tank sensor to indicate the liquid level. This sensor can also be programmed to pause spraying and return the drone to home base when the tank needs a refill. Once replenished, the drone flies back to continue spraying where it stopped. The maximum flying speed of multi-rotor drones varies between

10–30 miles per hour. They are usually flown 7–12 feet above the ground or crop canopy. Forestry applications may require the drone to fly over 30 feet above the ground to avoid obstacles. All current models of drones have a terrain sensor that maintains the optimum flight height to spray uneven and hilly terrain and automatically navigate hills and slopes. The price of spray drones varies between $20,000 and $40,000, depending on size, spraying capacity, manufacturer, and other features. Most spray drone models are compatible with Real Time Kinematics (RTK), which provides centimeter-level, locational precision during flight.

Best Spraying Practices Success in pesticide application is heavily dependent on knowing and following best spraying practices. Unfortunately, not much operational information is available for spray drones.

Drones for Spraying Pesticides—Opportunities and Challenges

However, many of the general principles for operating conventional piloted agricultural aircraft also apply to spray drones. One of the crucial determinations in aerial spraying is knowing the effective spray swath width so that each subsequent pass can be adjusted accordingly. Flight altitude affects the swath width, the quality of spray deposition into the target canopy, and the pesticide coverage on the canopy. Regardless of the spraying equipment used, there are two common ways to increase coverage on the target: 1. Reduce the droplet size. This option is not recommended for any type of aerial application because it can increase risk of drift. 2. Increase the gallons per acre application rate either by using a nozzle which has a higher flow rate capacity (gallons per minute), or by flying at a slower speed. However, increasing the gallons/acre application rate may require dilution of the spray mixture in the tank to ensure that the maximum active ingredient rate per acre

detailed in the product label is not exceeded. Another way to increase deposition of product applied in the target canopy is to minimize spray drift—the spray that leaves the target area without depositing on the target. Wind velocity is usually the most critical factor affecting drift. The greater the wind speed, the farther a droplet will deposit off-target. Even in light breezy wind conditions, leave a buffer zone between the area being sprayed and any field with sensitive crops downwind. Untreated areas can be sprayed when the wind is blowing away from the sensitive crops that are adjacent to the area being sprayed.

Flight altitude does not change the initial droplet size after it is released from the nozzle, but high altitudes expose the droplets to weather conditions such as wind, relative humidity, and temperature. This exposure increases drift potential of the droplets as their sizes get smaller. Also, smaller droplets may never reach their target under low relative humidity and high temperature conditions. To guard against these challenges, the flight height should be as close to the target as possible to reduce spray drift. However, always consider other unintended issues that may result from flying too low:

When spraying is completed, drones are usually folded up and secured properly to avoid any movement of the drone during transport. The drone should be secured in a separate compartment that is isolated from the driver of the vehicle and/or any passengers. When not in use, the spray drone should be stored in a locked and secure place away from any dwelling, people, or animals.

- safety of drone operation
- collision avoidance radar being frequently triggered, causing the drone to slow down or stop
- skips in spray deposition on the target that could significantly and negatively affect the efficacy of product applied, especially when spraying herbicides and defoliants

Acceptance of spray drones by individual farmers has been slow for several reasons:

There is not a universally accepted set of guidelines for the operation of spray drones, especially their optimum flight speed. According to one source (CropLife 2020), aerial spraying by a conventional, piloted airplane is normally conducted when the surface wind speed is less than 15 mph—a safe speed for aircraft handling. Spray drones are considerably lighter and may suffer problems at wind speeds more than 7 mph. The optimum speed of application for most multi-rotor spray drones is around 13 mph. These are 2020 guidelines, and they change from manufacturer to manufacturer for the various spray drone models. Therefore, it is best to operate a spray drone in the optimum conditions outlined in its operator manual.

Drones for Spraying Pesticides—Opportunities and Challenges

Limitations of Spray Drones and Obstacles to Their Adoption

- Not enough research data comparing drone performance (e.g., efficacy and spray drift) to ground sprayers and conventional aircraft is available. The limited published data on performance of spray drones may not be usable and can be contradictory because of the wide variation of design parameters among drones being tested.
- Fewer acres are covered per hour of operation compared to airplane and ground sprayers.
- The battery powering the drone lasts a short time (5–15 minutes with a full tank) and requires recharging between tank refills. Having three charged batteries per drone and fast charging at 240v eliminates long interruptions in spraying to charge the drone's battery. Maintaining three charged batteries allows replacement of a discharged battery while refilling the spray tank. The spent battery can then be

direct supervision of a person who holds this certificate. However, spraying pesticides in Ohio requires more than these two FAA certificates. An applicator must also complete the Ohio Commercial Pesticide Category 1 training course, which covers "the application of pesticides, except fumigants, by aircraft."

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Figure 9. "Swarm spraying" with drones.

recharged and ready for the next refilling.

- The FAA imposes several operational restrictions on drones, such as: a drone must weigh 55 pounds or less including its payload, the pilot flying the drone must maintain a visual line of sight with the drone, permission must be obtained when flying in restricted air space, and drones can be flown only from 30 minutes before sunrise to 30 minutes after sunset. Perhaps the most severe restriction is that an operator can fly only one drone at a time. However, swarm spraying (Figure 9) is practiced legally and successfully in other parts of the world, especially in southeast Asia, mainly China, South Korea, and Japan. Fortunately, the FAA allows pilots to apply for waivers for several of these limitations, such as the 55 lb maximum weight of the drone sprayer, night spraying, and maintaining a line of sight.
- Chemical product labels do not provide clear information 6 | Ohioline.osu.edu

related to drone spraying. Some labels do not allow aerial application of any form. Some labels allow aerial application of the product, but don't specify the type of aircraft that can be used. Currently, no pesticide label provides specific instructions on how the product can be sprayed using a drone. It is anticipated that pesticide labels will eventually refer to drone spraying. The EPA allows drone use for spraying if the pesticide is already labeled for conventional aerial application and if FAA rules for operating drones are followed.

Regulations Related to Using Drones to Spray Pesticides in Ohio Two certificates must be obtained from FAA to spray using drones: an FAA "Part 107 Certificate" to fly a drone and a "Part 137 Certificate" to apply pesticides using drones or to apply pesticides using drones while under the

Resources for Information on Obtaining Certificates to Apply Pesticides Using Drones Flying a drone is subject to many restrictions, including a requirement that the pilot be at least 16 years old and that the drone has a maximum weight of 55 pounds, unless an exemption is granted. To find out all the requirements to be a drone pilot, obtain the pilot certificate (FAA Part 107), and legally apply pesticides using a drone (part 137), visit the FAA web site at faa.gov/ uas/commercial_operators. Another informative and useful resource is the FAA Remote Pilot Study Guide at faa.gov/sites/faa. gov/files/regulations_policies/ handbooks_manuals/aviation/ remote_pilot_study_guide.pdf. Prospective pilots can also do an internet search for "FAA remote pilot study guide." Topics covered include airspace classification, operating requirements and flight restrictions, effects of weather on aircraft performance, emergency procedures, radio communication procedures, determining the performance of aircraft, physiological effects of drugs and alcohol on pilot performance, and registration and marking requirements.

Drones for Spraying Pesticides—Opportunities and Challenges

A web site prepared by Alan Leininger, Extension educator in Ohio, is also an excellent source of practical information related to drone spraying and the FAA requirements for certification to fly a drone. Leninger's website is located at henry.osu.edu/ program-areas/agriculture-andnatural-resources/precisionagriculture-technology. The Ohio Department of Agriculture's (ODA) website is another resource that includes information on the application of pesticides using drones. This website provides answers to many of frequently asked questions such as, "What pesticide licenses are required by ODA to apply pesticides via a UAV (aerial drone)?" It can be accessed at agri. ohio.gov/divisions/plant-health/ pesticides/uas/.

Future of Spray Drones Drone sprayers will never replace ground or conventional aerial application technology, but they may complement existing spray practices. The future of drone spraying will be mainly affected by the economics, timeliness of crop protection (i.e., which option may get the job done in the shortest time), the type of spraying to be done (broadcast vs. targeted), and availability of local companies offering drone spraying. Although drone spraying does not seem to be a viable option to compete with ground sprayers and conventional, piloted aircraft in the application of pesticides to large fields, some companies offering drone spraying indicate that their rates are competitive with or more economical than the cost of spraying done by ground equipment and conventional aircraft.

Acceptance and adoption rate of spray drones by individual farmers is likely to increase in the near future due to these changes in regulations and technological upgrades: 1. FAA regulations and restrictions on use of drones may be eased, especially restrictions on "swarming," in which multiple drones are operated by one pilot or autonomously. 2. Improved design and manufacturing may result in longer lasting batteries, wider spray width, higher flow rates, and faster operational speeds. 3. Larger drones with larger sprayer tanks may be

designed and possibly approved by the FAA. 4. Upgrades to drone technology may result in improved variable-rate application, precision spot spraying and route planning, and better obstacle avoidance. Even without the changes outlined above, spraying with available drones may be the best option under the following conditions:

- Up until 2023, the main use of spray drones in the United States was for fungicide application on wheat, corn, and some soybean acres. But spot spraying of tall weeds that survived a previously applied herbicide, as shown in Figure 10, is a concept that is being investigated at this point. Spot spraying of weeds with a drone can be much more efficient than spraying a whole field with typical ground equipment or a conventional aircraft. However, be aware that most herbicides are not labeled for use with spray drones currently, and none of the herbicides that can be used for post applications have approval by EPA for late-

season use. The cutoff date for most of such applications is early to midsummer at the latest. Spray drone operators are advised to check the information on the chemical label before spraying the product. In addition, it's questionable how effective herbicides would be on big weeds that presumably have some level of herbicide resistance.

- Portions of a field that cannot be reached by large, heavy ground sprayers because the soil is too wet, which happens frequently in some parts of Ohio, can be sprayed with drones.
- Drone spraying may be the best choice to avoid soil compaction and crop damage caused by ground equipment traffic when spraying fields with established crop canopies. Even after the wet ground dries enough to allow the large ground sprayer to get in the field, the sprayer is likely to cause a significant level of soil compaction resulting in reduced crop yield. Spot spraying, variable-rate spraying, or spraying a portion of the field that does not allow heavy equipment to get in the field, all can be accomplished easily with drone spraying technology. This usually is a twostep process. First a drone with an RGB or multispectral camera flies over the field and establishes the coordinates of the area to be sprayed or the operator maps out the areas to spray on a digital map by drawing polygons. The mapped areas are then uploaded to the flight plan of the spray drone. This drone then flies over the field and its nozzles spray pesticide when the drone reaches the appropriate GPS coordinates.

Dr. Jeff Stachler, Montana State University

Figure 10. Spot spraying with a drone to control weeds that survived the previously applied herbicide can be much more efficient than covering a whole field with typical ground equipment or conventional aircraft.

Summary and Suggestions Currently, there is tremendous interest in using drones to spray crop-protection products. Drones are now a viable option when choosing equipment to spray pesticides, and the number of companies offering drone spraying services is rapidly increasing in Ohio and other places in the United States. But is drone spraying a good option for everyone? If you are well informed about this technology, aware of all the rules and regulations, and have viable usages identified, then consider buying one. Otherwise, wait until you are adequately informed about all aspects of drone spraying. As is the case with other technologies in agriculture, developments in drone sprayer designs and capabilities are changing rapidly. Check websites of drone sprayer manufacturers to learn about the new features of their current models. Regulations too may change rapidly in the future because of the increasing interest in drone spraying and the high level of public demand for relaxation of

current rules and regulations. Universities, government research centers, and other independent research organizations are interested in conducting research to determine if drone sprayers provide pest control that is as effective as ground sprayers or aerial spraying using conventional aircraft. This research will provide much

more reliable information on this topic than what is available now. Stay up to date by regularly checking in with the appropriate resources:

- Stay informed on research, pesticide product labels, FAA and EPA regulations, and new drone designs.
- Visit the FAA website at faa.gov to check current regulations governing the use of spray drones.
- Remember that drone spraying is one form of aerial spraying, that people using spray drones must comply with aerial labeling, and that there have been no labels developed for spray drones yet. And, as always, contact the OSU Extension office in your county for additional information on

certification and licensing required to apply pesticides using any kind of sprayer, including drones.

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Reference CropLife International. 2020. “Drones Manual.” Brussels, Belgium: CropLife International. PDF. croplife.org/wp-content/ uploads/2020/03/Drones_Manual. pdf.

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Drones for Spraying Pesticides—Opportunities and Challenges

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Agriculture drones: A modern breakthrough in precision agriculture Vikram Puri * Guru Nanak University Regional Campus Jalandhar City 144007 Punjab India Anand Nayyar Department of Computer Applications & Information Technology KCL Institute of Management and Technology Jalandhar 144004 Punjab India Linesh Raja Department of Computer Science and Engineering Amity University Jaipur 303007 Rajasthan India Abstract Drones commonly referred, as UAVs are mostly associated with military, industry and other

specialized operations but with recent developments in area of sensors and Information Technology in last two decades the scope of drones has been widened to other areas like Agriculture. The drones manufactured these days are becoming smarter by integrating open source technology, smart sensors, better integration, more flight time, tracking down criminals, detecting forest and other disaster areas. The aim of this research paper is to highlight the importance of drones in agriculture and elaborate top drones available in market for Agriculture monitoring and observation for yielding better crop quality and preventing fields from any sort of damage. Keywords: Agriculture Drones, UAVs, Drones Mathematical Subject Classification: 68T40 *E-mail: vikrampuri@acm.org

©

- Introduction Unmanned Aerial Vehicles (UAVs) [1] [3] also commonly known as Drones are regarded as pilotless aircraft systems used in diverse applications like Industrial monitoring, photography, battlefield surveillance, air ambulance, package delivery and many more. Drones operated by single-operated pilot, are regarded as short distance flying objects, and on the other hand, there are long distance flying drones known for flying at High Altitude. Considering past few years, there has been considerable development in the area of drones for all possible kinds. Drones provide sophisticated advantages as compared to anything else like ease of use, accurate monitoring of those areas which are difficult to reach by man, illegal activities tracing, forest fire observations and surveillance of crop yields of large agriculture farms. Over the past 10-15 years, with high-end technology transformations from radio controlled model hobbyist's airplanes, drones are integrated with variety of functions. RF planes could not be controlled unless not seen by human eye but modern drones are fitted with GPS and camera which can be used by pilot to track and fly the drones to larger distances via making use of GPS enabled smartphones and even portable LCD enabled remote controls. With the integration of Wi-Fi technology in drones in form of First Person View (FPV), drones can be integrated with HD cameras like GoPro, DJI, Parrot and many others to stream real-time video of flight over smartphone or tablet. Currently, almost 85% of drone technology is mainly utilized by military and rest 15% by civilians for diverse applications. However,

Figure 1 Rotary Copter Drone being operated in Agriculture Field (Left) and Fixed Wing Drone (Right)

with certain restrictions and no fly zones, drones are also banned in some countries like India to fly over public places and government buildings. Association of Unmanned Aerial Systems International reported an annual growth of 85-92% every year especially in the upcoming market of Agriculture. Lots of researchers and drones manufacturing companies are either coming up or in process of releasing varied models of Drones especially made up for agriculture. Drones can be categorized in two categories: Fixed Wing Airplanes and Rotary Motor Helicopters Each of these drones has its own advantages and limitations. The fixed wing drones can fly at higher speeds ranging from 25-45 mph and can cover the range of 500 to 750 acres per hour depending on the battery. Rotary motor drones on the other hand can hover and focus on specific problem in real world and can fly over constant speed. They suffer from limited battery life and can take off and land off safely in small confined areas and are absolutely best for starters to learn Drone Flying. In this Research Paper, we primarily focus on importance of implementing and using Drones/UAV's in Agriculture and what additional benefits farmers can have on crop yield by using drones. Section 2 will cover application cum advantages of drones in agriculture; Section 3 highlights top drones, available specifically for agriculture. Section 4 covers conclusion and future scope. 2. Drones in Agriculture [2] Currently, the practical applications for drones are expanding from hobbyists to industries and other areas like photography etc. It is expected that Drones market can touch $200 billion by year 2020. Among various promising areas, Agriculture is regarded as one of the most important area where different varieties with feature packed facilities are required overcoming several challenges of farmers for better crop yield [4][5][6]. The following are the various Applications cum Advantages of using drones in Agriculture being deployed for day to day Agriculture tasks: 1. Agriculture Farm Analysis: Drones are high end reliable instruments flying in the sky and can be used by farmers to inspect the farm condition at the beginning of any crop year. Drones generate 3-D maps for soil analysis which is useful for

farmers to take care during seed ploughing. Soil and field analysis via drones also provides data useful for irrigation and managing nitrogen level of fields for better crop growth.

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- Time Saving: Farmers with tons of hectares of land finds difficult to reach each nook and corner of field for inspection time to time. Drones does this task without any hiccup as farmers can do regular air monitoring of field to know the status of their crops at regular intervals of time.
- Higher Agriculture Yield: The precision application of pesticides, water and use of fertilizers accurately monitored by drone will in turn increase the yield and overall quality can be taken care off. 4. GIS Mapping Integration: GIS Mapping has already proven its worth throughout the agriculture industry to manage resources, yield increase, input cost management, better business management and more. With GIS mapping integrated with Drones, the farmers can draw field borders for accurate flight pattern. 5. Imaging of Crop Health Status: With drones, crop health imaging can be done using Infrared, NVDI and multispectral sensors making the farmers better track the health of crop, transpiration rates and sunlight absorption rates etc. 3. Drones for Precision Agriculture [5] In this section, Agriculture Drones available in market are discussed along with their technical specifications. 3.1 Honeycomb AgDrone System The AgDrone System by Honeycomb Company is regarded as most sophisticated drone for Agriculture covering 600-800 acres of field every hour flying at 400 feet. The wings of the drone are composed of Kevlar

Figure 2 Honeycomb AgDrone

AGRICULTURE DRONES

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Table 1 Technical Specifications of Honeycomb AgDrone.

Parameters

Values

Drone type

Fixed Wing

Material

Kevlar Exoskeleton

Wingspan and Battery

49in; 8000 mAh LiPo

Coverage

858 Acres

Trigger Method

Automatic Dual Camera Electrical Signal

Flight Specifications

Cruise Speed: 46 km/hr Max Speed: 82 km/hr

[Src: http://www.honeycombcorp.com/agdrone-system]

Fiber composite, same material being used in Bulletproof jackets making the drone rugged for all conditions and in turn making it durable, versatile and powerful for agriculture 3.2 DJI Matrice 100 DJI Matrice 100 is regarded as the Best Quadcopter based Drone for Agriculture with dual battery support, which increases almost 40 minutes of flight times. Special features of this drone include GPS, Flight Controller, DJI Lightbridge which is regarded as Advanced Flight Navigation System to do complex tasks and easy to operate in all environmental conditions.

Figure 3 DJI Matrice 100 Quadcopter Drone

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Table 2 Technical Specifications of DJI Matrice 100 Quadcopter Drone

Parameters	Values
Drone type	Fixed Wing with Intelligent Flight Battery
Battery	5700 mAh LiPo 6S
Video Output	USB, HDMI-Mini
Flight Specifications	Max Speed: 5m/s (Ascent) Max Speed: 4m/s (Descent)
Operating Temperature	-10°c to 40°c

[Src: http://www.dji.com/matrice100]

Figure 4 DJI T600

3.3 DJI T600 Inspire 1 [7] The DJI T600 Inspire Quadcopter is another powerful carbon fiber material finish Agriculture drone known for its fast charging. It specially features 4K Video recording, individual flight and camera control and provides easy navigational capabilities. Table 3 Technical Specifications of DJI T600 Drone

Parameters	Values
Material	Carbon Fiber
Interface Type	Detachable
Battery	4500 mAh LiPo 6s

Contd...

Camera Features	Image: 4000x3000 ISO Range: 100-3200 (Video) 100-1600 (Photo) Modes (Photography): Single, Burst, Auto Exposure, TimeLapse Modes (Video): UHD, FHD, HD File Formats: JPEG, DNG, MP4, MOV Memory Card: 64GB (Max)
Flight Operations	Max Speed: 5 m/s (Ascent) Max Speed: 4 m/s (Descent)
Flight Time	18 min / 40 Min with Additional Battery

[Src: http://www.dji.com/inspire-1]

3.4 Agras MG-1- DJI Agras MG-1 – DJI is ultimate octocopter designed to assisting farmers to spray large areas of farmland with pesticides, insecticides or Fertilizers. The unique features of this drone is that MG-1 is compatible to carry upto 10KG of liquid payloads and can cover 4000-6000 m2 area in just 10 minutes which is regarded as 70 times faster as compared to manual spraying. MG-1 has fully sealed body and consists of

efficient, integrated centrifugal cooling system to keep the air flowing to each part of the Drone during flight time. MG-1 is equipped with 4 nozzles for accurate spraying of fertilizer in the field and is fully equipped with three types of Flight Mode: Smart, Manual Plus Mode and Manual Mode depending on specifications of field. MG-1 features Y-type folding structure without making use of any additional tools [8].

Figure 5 Agras MG-1-DJI

Table 4 Technical Specification of Agras MG-1-DJI

Parameters	Values
Material	High Performance Engineered Plastics
Liquid Tank	10 Kg (Payload), 10 L (Volume)
Nozzle	4
Battery	MG-12000
Flight Parameters	Max Take Off Weight: 24.5 Kg Max Operating Speed: 8m/s Max Flying Speed: 22 m/s Operating Temperature: 0 to 40 oC

[Src: https://www.dji.com/mg-1]

3.5 EBEE SQ- SenseFly The EBEE SQ is High Performance agriculture drone especially designed for Crop Monitoring from planting to harvest to assist farmers in better crop yield. This drone is fully integrated and highly precise and has multispectral sensor capable for capturing data across four nonvisible bands along with RGB imagery in just single flight. The drone provides larger coverage as compared to other quadcopter drones and has automatic 3D flight planning. The drone is fully compatible with Pix4dmapper AG mapping software to create NVDI maps for crop fields and identify problem areas during flight.

Figure 6 EBEE SQ-SenseFly

Table 5 Technical Specifications of EBEE SQ-Sense Fly

Parameters	Values
Drone Type	Detachable Wings with Low-Noise, Brushless and Electric Motor
Flight Operations	Max Flight Time: 55 Minutes Linear Landing with ~ 5m Flight Planning Software: eMotion Ag
Sensors	4 Spectral Sensors, GPS, IMU, Magnetometer, SD Card
Camera	4-1.2 MP Spectral Camera 1fps 16MP RGB Camera

[Src: https://www.sensefly.com/drones/ebee-sq.html]

3.6 Lancaster 5 Precision Hawk Lancaster 5 Precision Hawk is among one of the Autonomous Drones especially designed for Agriculture and Environmental Monitoring and has capability to optimize flight plan to collect data in most sophisticated way. With the integration of smart flight controls, the drone adjusts accordingly to payloads and unpredictable environmental conditions to bring back the best data of flight operation. Consists of Plug and Play sensors to deliver more data to the user as per the user application specifications. The drone has in built sensors like Humidity, Temperature, Pressure as well as incident light. As the drone supports open source technology, it gives wide open doors for researchers to contribute their own sensor code.

Figure 7 Lancaster 5 Precision Hawk

Table 6 Technical Specifications of Lancaster 5 Precision Hawk

Parameters	Values
CPU	720 MHz Dual Core Linux CPU
Interfaces	Analog, Digital, Wi-Fi, Ethernet, USB
Wing	Fixed Wing with Single Electric Motor
Battery	7000 mAhr
Flight Parameters	Altitude: 2500 m Max Speed: 79 km/hr Survey Span: 50-300 m
Operating Temperature	40oC

[Src: http://www.precisionhawk.com/lancaster]

3.7 SOLO AGCO Edition The SOLO AGCO Edition is regarded as till date most optimal solution via drone for better farm management. The drone is fully autonomous in flying and provides better high-resolution aerial maps to assist the farmers in monitoring field condition efficiently. It makes use of intuitive mission planning and cloud based high-resolution mapping software to increase flight efficiency. Drone makes use of Agribotix imaging and analysis software for precision agriculture.

Figure 8 SOLO AGCO Edition

Table 7 Technical Specifications of SOLO AGCO Edition

Parameters	Values
Flight Controller	PIXHAWK 2
Material	Self-Tightening Glass-Fortified Nylon Props
CPU	1 GHz Onboard Computer

Video

Full HD Streaming to Mobile Device

Flight Parameters

Max Speed: 55 mph Flight Time: 25 Minutes Auto Take Off and Landing

Camera

2 Cameras- GoPro 4 Hero4 Silver for RGB NIR GoPro

Others

Field Health Mapping (NDVI) Management Zone Mapping

[SRC: https://www.pages05.net/agco/SOLO_UAV/contact/]

- Conclusion The market for Drones is expanding day by day from the last two decades and they have brought a significant revolution in the area of Industry, Military, Agriculture and many more. This study investigated the importance of drones in Agriculture and has highlighted the various drones available for diverse agriculture applications along with technical specifications. The paper is regarded as eye-opener for Industry and Agriculture for development and integration of more drones for making Agriculture tasks better and in turn yielding best crop quality in near future References [1] Grenzdörffer, G. J., Engel, A., & Teichert, B. (2008). The photogrammetric potential of low-cost UAVs in forestry and agriculture. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 31(B3), 1207-1214. [2] Stehr, N. J. (2015). Drones: The Newest Technology for Precision Agriculture. Natural Sciences Education, 44(1), 89-91. [3] Eisenbeiss, H. (2004). A mini unmanned aerial vehicle (UAV): system overview and image acquisition. International Archives of

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Guest Editorial Can Drones Deliver

IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, VOL. 11, NO. 3, JULY 2014

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Guest Editorial Can Drones Deliver?

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RONES, autonomous or teleoperated flying machines, have been an active area of research for decades. In my area of research—dynamics and control—flying machines offer a unique challenge: they are relatively straightforward to model in steady conditions, but defy pragmatic first-principles modeling approaches during high-performance maneuvers. They are thus ideal test beds for bridging traditional model-based automation and control approaches with modern data-driven ones. Drones have recently captured the imagination of the general public. In December 2013, Jeff Bezos, CEO and founder of Amazon.com, announced on the “60 Minutes” show that drones could be used to speed delivery of packages to consumers. As of April 2014, the “Amazon Prime Air” video received more than 14 million views on YouTube and stimulated speculation and discussions

around the world. There was interest in small flying machines as a means of delivering payloads well before this announcement. For example, in early 2009 my research group started receiving a large number of e-mails from would-be entrepreneurs, asking us if we could help them develop a pizza delivery system using drones. Why us? When I moved to ETH Zurich in late 2007, we created the Flying Machine Arena (FMA), "a space where flying robots live and learn."1 We started to release videos of quadcopters performing athletic feats in early 2009, and this attracted people with aspirations to monetize these capabilities. After pizzas came burritos and a wide variety of other fast foods, but also document delivery, and even goods to hikers in the Swiss Alps. I received a more serious inquiry from the folks at Matternet in late 2011.2 Their vision was to create a transportation network based on flying machines, and to initially address niche markets such as medicine delivery in underdeveloped and hard to reach areas. Unlike all the people who had contacted me to date on the subject, Andreas Raptopoulos, one of the Matternet founders, had connected my work on flying machines with Kiva Systems, the robotics and logistics company that I co-founded with Mick Mountz and Pete Wurman. In a Kiva warehouse, hundreds of Digital Object Identifier 10.1109/TASE.2014.2326952 1The roots of the FMA can be traced back to the late 90s and early 00s: The

system architecture is modeled after the Cornell RoboCup team, and many early prototypes involving quadcopters were developed at Cornell at that time. 2Matternet is a spinoff from Singularity University, a private institution offering executive education, whose mission is to "educate, inspire, and empower leaders to apply exponential technologies to address humanity's grand challenges."

autonomous mobile robots move inventory in distribution facilities. What Matternet wanted to do was basically Kiva Systems in the open air. Coincidentally, as it relates to this story, Kiva was bought by Amazon in 2012.3 Impressed by Andreas' tenacity and entrepreneurial energy, in early 2012 I did a feasibility analysis of package delivery for his upcoming Solve for X talk, "Andreas Raptopoulos on physical transport."4 Part of this analysis, which addressed the feasibility and costs associated with energy and power, is included below.5 The very high-level operating assumptions were the following: 1) Payload of up to 2 kg. 2) Range6 of 10 km with headwinds of up to 30 km/h. It was assumed that these would be battery powered vehicles for the simple reason that many economic factors were pushing to improve the performance and reduce the cost of battery technology, an assumption that has since been validated by the tremendous success of Tesla Motors and their battery powered vehicles, and the recent announcement by its founder and CEO Elon Musk of a new "gigafactory" for battery production that will drive costs down by more than 30%. Let's first explore feasibility. The power consumption in kW can be approximated by (1) where payload mass, in kg; vehicle mass, in kg; lift-to-drag ratio; power transfer efficiency for motor and propeller; power consumption of electronics, in kW; cruising velocity, in km/h. 3Also coincidentally, several of Kiva's early hires were former Cornell graduate students with quadcopter and flying machine expertise. As a result, quadcopters were a topic of water cooler conversation at Kiva since its early days, and one of our old decommissioned quadcopter prototypes from Cornell graced Kiva's electrical engineering work area. 4Solve for X is an effort launched by Astro Teller and co-workers at Google on the Google[x] team "to accelerate progress on technology moonshots." 5The full analysis included vehicle and system architecture, overall system costs, safety considerations, and vehicle routing. 6In the Matternet scenario vehicles fly from charging station to charging station, so the range is the maximum distance that a vehicle can fly on a single charge.

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Some numbers: the payload mass is set to 2 kg; we assume a vehicle mass of 4 kg, more on this later; the lift-to-drag ratio is set to 3, a pessimistic value, and is meant to capture a vehicle that is capable of vertical takeoff and landing (for comparison purposes, a typical helicopter has an effective lift-to-drag ratio greater than 4); the power transfer efficiency is set to 0.5; the power consumed by the electronics (which includes all sensors) is assumed to be 0.1 kW, and is roughly comparable to a very powerful laptop computer; the cruising velocity is set to 45 km/h. These numbers result in a power consumption value of 0.59 kW. A high-end lithium ion battery has a specific power of 0.35 kW/kg, and thus a 2 kg battery could provide as much as 0.7 kW. This leaves 2 kg for the remainder of the vehicle, a significant, but not unreasonable, value.7 The worst-case energy requirement in kW h can be approximated by (2) where maximum range, in km; ratio of headwind to airspeed.

Again some numbers: the maximum range is set to 10 km, while an air speed of 45 km/h and a headwind of 30 km/h result . These numbers, and the previous values, yield in an energy requirement of 0.39 kW h. A high-end lithium-ion battery has a specific energy of 0.25 kW h/kg, and thus a 2 kg battery would suffice. We now address the economics. The average energy cost per kilometer can be approximated by

(3) where cost of electricity, in $/kW h; charging efficiency. The cost of electricity is assumed to be 0.1 $/kW h, a rough average of the retail cost in the United States, while the charging efficiency is assumed to be 0.8. These numbers, and the previous values, yield a cost of roughly 0.2 cents per km for a 2 kg payload, a surprisingly low amount.8 We next look at the operating cost associated with the batteries, which are assumed to dominate the total vehicle operating costs in the long run, once the vehicles reach a level of 7The battery, or “fuel,” and the payload amount to 2/3 of the total vehicle mass, which is comparable to long-haul commercial airliners. 8We were similarly surprised when assessing Kiva’s feasibility to learn that running a mobile robot in a 24/7 setting would only result in an electricity bill of 25 cents a day. The takeaway here is that electricity in the United States is too cheap, and does not fully reflect the real and sustaining costs to generate it.

maturity comparable to today’s automobiles.9 The average battery cost per km can be approximated by (4) where battery cost, in $/kW h; life of battery, in cycles. A high-end lithium-ion battery costs roughly $300/kW h, and can be cycled about 500 times, resulting in a cost of roughly 0.8 cents per km for a 2 kg payload. The total cost of batteries and power is thus 1 cent per km for a 2 kg payload. So, is package delivery using flying machines feasible? From a cost perspective, the numbers do not look unreasonable: the operating costs directly associated with the vehicle are on the order of 10 cents for a 2 kg payload and a 10 km range. I compare this to the 60 cents per item that we used over a decade ago in our Kiva business plan for the total cost of delivery, and it does not seem outlandish. To make drone delivery practical, automation research is needed to address three main challenges: vehicle design, localization and navigation, and vehicle coordination. Vehicle design encompasses creating machines that are efficient, (most probably) can hover, can operate in a wide range of conditions, and whose reliability rivals that of commercial airliners; this is a significant undertaking that will require many iterations, and the ingenuity and contributions from folks in diverse areas. Localization and navigation may seem like solved problems because of the many GPS-enabled platforms that already exist, but delivering packages reliably, in different operating conditions, in unstructured and changing environments, will require the integration of low-cost sensors and positioning systems that either do not yet exist, or are still in development. Finally, thousands of autonomous agents in the air, sharing resources such as charging stations, will require robust coordination which can be studied in simulation. In the medium to long term, I am optimistic. Additional challenges include initial public reactions, privacy concerns, and government regulation. These will be tough to overcome. Having said that, I believe that ultimately the concerted efforts and lobbying by the many stakeholders who will benefit from goods being delivered by flying machines will result in packages flying above our heads in the not so distant future. For better or for worse. RAFFAELLO D’ANDREA, Guest Editor ETH Zurich Zurich, 8092 Switzerland rdandrea@ethz.ch Founder, Verity Studios Co-Founder, Kiva Systems 9I never cease to be amazed by the robustness and reliability of today’s cars: except for consumables such as fuel, fluids, and tires, an automobile needs very little maintenance.

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Inviting-Comments-on-Draft-SOPs-merged

Crop Specific SOPs for Application of pesticide with drones DRAFT REPORT

Crop Specific SOPs for Application of Pesticides with Drones

Submitted to

(Mechanization and Technology Division) Department of Agriculture and Farmers Welfare Ministry of Agriculture & Farmers Welfare Government of India

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Crop Specific SOPs for Application of pesticide with drones

Crop Specific SOPs for Application of Pesticides with Drones

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Crop Specific SOPs for Application of pesticide with drones

Preface Modern crop production and management for sustainable and profitable agriculture requires an early information system to know about crop health condition. Similarly, the quick response to address the undesirable damages caused by biotic and abiotic stresses is important to minimize the losses. Labour shortage and increased input cost of crop production is another challenge that needs to be addressed immediately. So judicious use of inputs by precision methods of applications is need of the hour. Unmanned aerial vehicles (UAVs), commonly known as “drones” can effectively be used for application of crop inputs (Plant protection and crop nutrients). Aerial spraying using drones saves huge time and labour requirement and thus allows large areas to be treated in very short times. Spraying through drones can be carried out when field conditions prevent movement of man and ground machines. It enables the timeliness of spray treatments without inflicting soil compaction. Drones can be used for timely detection of insects and pests, crop health monitoring, targeted input application, and rapid assessment of crop yield and crop losses. There are, however, certain disadvantages associated with drone spraying. High wind speed and temperature inversion may limit

treatment application whilst trees, waterways, environmental considerations and overhead power lines may also prevent some fields from being treated. Volatility and spray drift are problems associated with drone spraying which can lead to environmental contamination, if spraying is incorrectly executed. Also, unsafe piloting of drones may cause security concerns of the operators and others. Furthermore, in order to maximize the crop production from the minimum crop inputs under prevailing climatic conditions, need-based, location specific technology are required. To make drone spraying popular, Optimum bioefficacy and no phytotoxicity must be ensured. In fact any technology including drone assisted spraying has to be explored for potential use in different crops and for different agro-climatic zones. Thus, to widen the scope of drone assisted pesticide application for different crops grown under diverse climatic conditions, there is urgent need to have crop specific SOPs taking into considerations the relevant parameters like temperature, humidity, wind speed, terrain and crop as well as other environmental parameters.

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Crop Specific SOPs for Application of pesticide with drones

In view of the above, a committee was constituted by Department of Agriculture, & Farmers Welfare (M& T Division), Ministry of Agriculture & Farmers Welfare, Government of India vide letter No. F1310/2022-M&T(I&P) dated 26/07/2022) to prepare the crop specific “Standard Operational Procedures (SOPs)” for Application of pesticide with Drones.

Composition of the committee : 1.

Dr. Indra Mani, Vice Chancellor, Vasant Rao NaikMarathwadaKrishiVidhyapeeth, Parbhani (Maharashtra) [Chairman] 2. Er. C. R. Lohi, Deputy Commisioner (M&T), Krishi Bhawan, New Delhi [MemberSecretary] 3. Dr. Archana Sinha, Joint Director, Plant Protection division, DA&FW, New Delhi [Member] 4. Dr. R. N. Sahoo, Principal Scientist, Division of Agricultural Physics , IARI, New Delhi[Member] 5. Dr. Sunil D. Gorantiwar, Professor and Head Agril. Engg., MPKV, Rahuri [Member] 6. Dr. A. Sambaiah, Sr. Scientist (Ag. Engg.) ANGRAU), Guntur, AP [Member] 7. Dr. Dilip Kumar Kushwaha, Scientist, Division of Agricultural Engineering, IARI, New Delhi [Member] 8. Dr. S. Pazhanivelan, Director, Water Technology Centre, TNAU, Coimbotore, TN [Member] 9. Dr. Ram Gopal Verma, Entomologist, PJTSAU, Hyderabad,Telangana [Member] As per the office memorandum, the Chairman of the committee may consult any expert from the Drone and Pesticide Industries, SAUs and ICAR Institutes, IITs, etc. Accordingly, Chairman co-opted the following experts from ICAR institutes, SAUs and , Industry 1. 2. 3. 4. 5. 6.

Dr. Roaf Ahmad Parray, Scientist, Division of Agricultural Engineering, ICAR-IARI, New Delhi Dr. Subhash Chander, Director, ICAR - National Centre for Integrated Pest Management, Pusa Campus, New Delhi Dr. V. K. Baranwal, Professor Emeritus (ICAR) , Division of Pathology, ICAR-IARI, New Delhi Dr. Sushil Desai, Crop Science Division, Bayer Crop Science Ltd, New Delhi Dr N.K. Bhute, CAAST-CSAWM, MPKV, Rahuri, Maharastra Dr. Anoop Kumar Upadhyay, IoTech World, Gurugram, Haryana

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Crop Specific SOPs for Application of pesticide with drones

Terms of Reference a.

The crop-wise SOPs will be developed as an extension to the existing SOP (for use of Drone Application with pesticides for the crop protection and for spraying soil and crop nutrients in Agricultural, Forestry, Non crop areas) of Ministry of Agriculture & Farmers Welfare, Government of India, which will include the technical operational and safety requirements to ensure the safe, efficient and effective use of inputs and the technology. The committee will complete the work and submit the final draft of the SOPs on or before 30 th

b.

September 2022. c.

The chairman of the committee may consult any expert form the Drone and Pesticide Industries, SAUs and ICAR Institutes, IITs, etc.

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- Methodology for collection of information on drone based spraying application for development of SOPs The methodology followed for data collection for preparation of crop specific Standard Operating Procedures (SOP) involved scientific deliberations and information collection through online survey schedule. The committee members along with co-opted members and industry representatives held many scientific deliberations on the type of experimental data required for preparation of crop specific Standard Operating Procedures (SOPs) for application of drones. Based upon the input from different members, a survey schedule was prepared for collection of information from different ICAR Institutes, SAU's and private industries working on different aspects of drone assisted chemical application. The survey schedule contained detailed information about the experimental location, environmental conditions, chemical formulations, drone and spraying systemspecifications, operational conditions, observational parameters, phyto-toxicity, bio-efficacy and other critical observations (Proforma: Annexure-I). The developed survey schedule was sent to different SAU'S, ICAR Institutes and private industries for submission of experimental data related to drone assisted chemical application carried at their respective centres. In order to facilitate online submission of information, a Google form page of survey schedule was also created. The link of same was shared with different research institutes and stakeholders to submit information online. In total, seventy-seven (77) responses were received from different research institutions covering experimental data on drone assisted pesticide application in different crops(Annexure-II). The information received was systematically arranged and classified crop-wise and pesticide wise. Overall, the information was received for nine major crops i.e. rice, maize, cotton, groundnut, pigeon pea, safflower, sesame, soybean and sugarcane. Based on the available information for the crops, the specific SOPs were developed for application of different pesticides through use of drones. The crop specific SOPs mostly focuses on crop canopy volume, crop growth stages, pesticide concentration, dosage, water volume per hectare, drone height above crop canopy, flight speed and spray discharge rate.

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- Crop Specific SOPs for selected nine crops The data was received for nine major crops i.e. rice, maize, cotton, groundnut, pigeon pea, safflower, sesame, soybean and sugarcane. Based on the available information, the crop specific SOPs were developed for application of different pesticides/ fungicides through use of drones. The SOPs are mainly based on drone parameters (Drone flying speed, height of drone above the crop canopy), sprayer parameters (nozzle and swath characteristics), crop parameters (crop canopy volume, crop growth stages, water volume per hectare, pesticide concentration and dosage, suitable time of spray), ambient conditions & location (temperature, humidity, wind speed and climatic zone) with major emphasis laid on performance parameters (bio-efficacy and phytotoxicity). The crop specific SOPs were developed considering a standard drone with tank capacity of 10 liters and overall weight of the drone less than 25 kg. The height of the drone above the crop canopy is related to overall weight of the drone, downwash effect over the crop canopy and sprayer characteristics. The drone has to fly near the crop canopy as much as possible to avoid drift during operation and to save the environment. However, the turbulence created by drone should not lead to lodging of crop. Therefore, operation at optimum height is important. Similarly, the drone flight speed affects the uniformity of spray and needs to be optimized .The procedure for the selection of the drone speed and nozzle height from the crop canopy is given in Annexure –II. As per the data received for different crops, no crop damage or phytotoxicity was observed at tested concentrations of the selected pesticides () at different doses (1X and 2X) and their respective combinations when sprayed using drones. The experiments in above regard were conducted in Southern Plateau and Hills, Trans – Gangetic Plains Agro-climatic region by selected institutes.

Crop Specific SOPs Table-1(A) : Crop Specific SOP for rice

- Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

4.5-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm - 6pm 8am-11 am & 2pm-6pm 6am -11am < 35°C > 50% < 3m/s Don not spray Do not operate Yes Yes

Safety requirements for efficient and effective use of the inputs

Do not spray crop with pesticides during flowering. Pesticide can damage flower resulting in empty grains and also kill beneficial insects. If necessary to spray (unevenflowering + milk stage) it should be done during colder parts of the day when flowers are closed.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(B): Crop Specific SOP for cotton 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc.

4.5-5.0 <5.5

Good standing crops Varieties prone to lodge

1.5-2.5 2.0-2.5

Stage-1 : Early stage Stage-2: Full canopy stage

20 25

- Height above crop canopy (m)
- Water volume (l/ha)
- Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar):

Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3

- Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

6am -10 am & 3pm - 6pm 8am-11 am & 2pm-6pm < 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Safety requirements for efficient and effective use of the inputs

Avoid chemical insecticides during the first two months of the crop. During initial phase of crop growth, natural enemies prey on sucking pests as well as eggs of lepidopteran pests. Avoiding chemical sprays during this period helps to conserve naturally occurring biological control agents that help to keep pest population under check.

Do not use WHO Class 1a and Class 1b insecticides (Extremely and Highly hazardous category).

Avoid Pyrethroids during the first 4 months after sowing. Pyrethroids may be used only late in the season as one or at the most two sprays for the control of pink bollworm.

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Crop Specific SOPs for Application of pesticide with drones

Not to spray against minor lepidopteran insects such as the cotton leaf folder, Syleptaderogataand cotton semilooper, Anomisflava. These insect larvae cause negligible damage to cotton but serve as hosts for parasitoids such as Trichogrammaspp., Apantelesspp and Sysiropaformosa, that attack H. Armigeraand other bollworms. Minimum foliar sprays of neonicotinoid insecticides such as Acetamiprid, Imidacloprid, Clothianidin and Thiomethoxam which are likely to aggravate insect resistance, since Bt cotton hybrid cotton seeds are treated with neonicotinoids.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(C): Crop Specific SOP for maize . Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/m) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season: Winter season:

4.5-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm -6pm 8am-11 am & 2pm-6pm

*Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

6am -11am

< 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Safety requirements for efficient and effective use of the inputs

As the larvae of Army worm are active at night, spraying in the evening is more advantageous.

Spraying chemical insecticides early in the crop cycle are most likely to kill off the natural enemies and may not be economical.

Precautions for pesticide use: Not more than two chemical sprays are to be used in entire crop duration. Same chemical should not be chosen for second spray. Sprays should always be directed towards whorl and applied either in early hours of the day or in the evening time.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(D): Crop Specific SOP for groundnut 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season:

4.5-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm -6pm 8am-11 am & 2pm-6 pm

*Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

< 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Safety requirements for efficient and effective use of the inputs

In case of pests which are active during night like Spodoptera spray recommended biocides chemicals at the time of their appearance during dusky hours.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(E): Crop Specific SOP for pigeon pea 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (l/m) Angle: Swath: Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

4.0-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm -6pm 8am-11 am & 2pm-6pm 6am -11am

< 35°C > 50% < 3m/s Don not spray Do not operate

Safety requirements for efficient and effective use of the inputs

Do not spray in hot or windy conditions.

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yes yes

Crop Specific SOPs for Application of pesticide with drones

Table-1(F): Crop Specific SOP for safflower 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors Safety requirements for efficient and effective use of the inputs

4.5-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm -6pm 8am-11 am & 2pm-6pm 6am -11am < 35°C > 50% < 3m/s Don not spray Do not operate yes yes

In case of pests which are active during night spray recommended biopesticides/ chemicals at the time of their appearance in the evening.

Do not spray pesticides at midday as most of the insects are not active during this period.

Emulsifiable concentrate formulations should not be used for spraying with battery operated ULV sprayer Enhance parasitic activity by avoiding chemical spray, when 1-2 larval parasitoids are observed. Safflower is basically self-pollinated but bees or other insects are generally necessary for optimum fertilization and maximum yield so insecticide spray should be avoided at flowering.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(G): Crop Specific SOP for sesame 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 :

Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

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4.5-5.0 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm-pm 8am-11am & 2pm-6pm 6am -11am

< 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Crop Specific SOPs for Application of pesticide with drones

Table-1(H): Crop Specific SOP for soybean 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season:

3.5-4.5 <5.5 1.5-2.5 2.0-2.5 20 25 Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3 6am -10 am & 3pm-pm 8am-11 am & 2pm-6pm

*Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors Safety requirements for efficient and effective use of the inputs

6am -11am

< 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Spray operation should be carried out either in morning or late evening hours, as during day time larvae of Spodoptera hide in the soil crevices. This will also avoid adverse effect on parasitoids and predators Although soybean is a self-pollinated crop, pollinators visit soybean fields regularly during the crop's flowering stage. These pollinators are at danger from insecticide sprays; so follow pest management strategy, avoid spraying or little insecticide should be sprayed at flowering.

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Crop Specific SOPs for Application of pesticide with drones

Table-1(I): Crop Specific SOP for sugarcane 1. Drone Flying Speed (m/s) During spraying During turning, RTL etc.

4.5-5.0 <5.5

Good standing crops Varieties prone to lodge

3.0-4.0 -

Stage-1 : Early stage Stage-2: Full canopy stage

20 25

- Height above crop canopy (m)
- Water volume (l/ha)
- Nozzles Type of nozzle Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (litre/min) Angle: Swath(m): Number of nozzles: Pressure(bar):

Anti-drift Flat fan 250-350 250-350 0.3-0.6 60-120 3-6 4-6 2-3

- Suitable Time of spray Summer and rainy season:

Winter season: *Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

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6am -10 am & 3pm-6pm 8am-11am & 2pm-6 pm < 35°C > 50% < 3m/s Don not spray Do not operate yes yes

Crop Specific SOPs for Application of pesticide with drones Table-2: Summary sheet of SOPs for selected nine crops S.No.

- Drone Flying Speed (m/s) During spraying During turning, RTL etc. 2. Height above crop canopy (m) Good standing crops Varieties prone to lodge 3. Water volume (l/ha) Stage-1 : Early stage Stage-2: Full canopy stage 4. Nozzles Type of nozzle

Droplet Size (µm): Insecticide Droplet Size (µm): Fungicide Nozzle discharge rate (l/m) Angle: Swath: Number of nozzles: Pressure(bar): 5. Suitable Time of spray Summer and rainy season:

Winter season:

*Strictly avoid spraying during flowering stage 6.Environmental conditions Temperature Humidity Wind speed During rain If visibility during Fog/mist is not good 7.Site Specific Plain land: Take care of obstacles present in the field Sloppy terrain: Use terrain following sensors

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1 Rice

2 Cotton

3 Maize

4 Groundnut

5 Pigeon pea

6 Safflower

7 Sesame

8 Soybean

9 Sugarcane

4.5-5.0 <5.5

4.5-5.0 <5.5

4.5-5.0 <5.5

4.5-5.0 <5.5

4.0-5.0 <5.5

4.5-5.0 <5.5

4.5-5.0 <5.5

3.5-4.5 <5.5

4.5-5.0 <5.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

1.5-2.5 2.0-2.5

3.0-4.0 -

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Antidrift Flat fan 250-350

Antidrift Flat fan 250-350

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250-350

250-350

250-350

250-350

250-350

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

0.3-0.6

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

60-120 3-6 4-6 2-3

6am -10 am & 3pm 6pm

6am -10 am & 3pm 6pm

6am -10 am & 3pm 6pm

6am -10 am & 3pm 6pm

6am -10 am & 3pm 6pm

6am -10 am & 3pm 6pm

6am -10 am & 3pmpm

6am -10 am & 3pmpm

6am -10 am & 3pm6pm

8am-11 am & 2pm6pm

8am-11 am & 2pm6pm

8am-11 am & 2pm-6pm

8am-11 am & 2pm-6 pm

8am-11 am & 2pm6pm

8am-11 am & 2pm-6pm

8am11am & 2pm6pm

8am-11 am & 2pm6pm

8am-11am & 2pm-6 pm

6am 11am

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6am 11am

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6am 11am

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-

< 35°C > 50% < 3m/s Don not spray Do not operate

< 35°C > 50% < 3m/s Don not spray Do not operate

< 35°C > 50% < 3m/s Don not spray Do not operate

< 35°C > 50% < 3m/s Don not spray Do not operate

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< 35°C > 50% < 3m/s Don not spray Do not operate

< 35°C > 50% < 3m/s Don not spray Do not operate

< 35°C > 50% < 3m/s Don not spray Do not operate

yes

Yes

Yes

Yes

yes

yes

Yes

yes

yes

yes

Yes

Yes

Yes

Yes

yes

Yes

yes

yes

250-350

Crop Specific SOPs for Application of pesticide with drones

Table-3: The crop wise list of pesticide molecules tested for phytotoxicity (crop safety) using drones Crop Rice

Insecticides, Fungicides alone & in combinations Chlorantraniliprole 18.5SC, Tebuconazole 50 + Trifloxystrobin 25 (75WG), Propiconazole 25EC, Azoxystrobin 18.2 + Difenoconazole 11.4SC, Picoxystrobin 7 + Propiconazole 12 SC, Chlorantraniliprole 18.5SC and (Tebuconazole 50 + Trifloxystrobin 25 - 75 WG), Chlorantraniliprole 18.5SC and (Picoxystrobin 7 + Propiconazole 12 SC), Chlorantraniliprole 18.5SC and (Flupyroxad 62.5 + Epoxiconazole 62.5EC), Chlorantraniliprole 18.5SC and (Azoxystrobin 18.2 + Difenoconazole 11.4SC), (Acephate 50 + Imidacloprid 1.8 SP) and (Mancozeb 50 + Carbendazim 25 WP), Triflumezopyrim 10SC, Pymetrozine 50WG, Dinotefuran 50SG, Cartap hydrochloride 50SP and Mancozeb 50 + Carbendazim 25 WP. Flonicamid 50 WG, Spinetoram 11.7SC, Monocrotophos 36SL, Profenophos 50EC, Cotton Acephate 75SP, Diafenthiuron 50WP, Fipronil 5SC, Imidacloprid 17.8SL, Acetamiprid 20 SP, Carbendazim 50WP, Propiconaozole 25EC, Kresoxim

methyl 44.3SC, Chlopyriphos 50 + Cypermethrin 5EC, Tebuconazole 50 + Trifloxystrobin 25 Metiram 55 + Pyraclostrobin 5, , Azoxystrobin 18.2 + Difenoconazole 11.4SC Monocrotophos 36SL, Quinalphos 25EC, Chlorantraniliprole 18.5SC, Flubendiamide Redgram (Pigeonpea) 39.35SC, Indoxacarb 14.50SC, Emamectin Benzoate 5SG, Spinosad 45SC, Novaluron 5.25 + Indoxacarb 4.50SC, and Chlorantraniliprole 9.30 + Lambda-cyhalothrin 4.6 ZC Groundnut Tebuconazole 25.9EC, Chlorantraniliprole 18.5SC and Tebuconazole 25.9EC Chlorantraniliprole 18.5SC, Chlorantraniliprole 18.5SC Soybean *For the maize and sapflower crops, no phytotoxicity was observed. However, the chemicals used were not included in the CIBRC's recommended pesticide. *For sugarcane crop the SOPs are only for drone operating and spraying system parameters (as phtotoxicity and bioefficacy data was not available).

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Crop Specific SOPs for Application of pesticide with drones

General Guidelines for pest management in crops with drone assisted spraying

Do not spray if there is forecast of heavy rains in next 1-2 days

Avoid broad-spectrum insecticides when a narrow-spectrum or more specific insecticide will work. More preference should be given to green labeled insecticides.

Alternate different insecticide classes: Avoid the repeated use of the same insecticide, insecticides in the same chemical class, or insecticides in different classes with same mode of action and rotate/alternate insecticide classes and modes of action.

Insecticides should be used only as a last resort when all other non-chemical management options are exhausted and P: D ratio is above 2: 1.

Apply biopesticides/chemical insecticides judiciously after observing unfavourable P: D ratio and when the pests are in most vulnerable life stage. Use application rates and intervals as per label claim.

Use protective clothing, facemask and gloves during preparation and application of pesticides.

Enter the field only 48 hours after spraying pesticide.Interval between application of chemical insecticide and harvest of maize corn should be minimum 30 days

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Crop Specific SOPs for Application of pesticide with drones

Annexure-I Ready-Reckoner to determine drone flying and spraying parameters

Following table may be used as ready reckoner to set the drone flying speed for uniform spray applying based on swath, nozzle discharge and water volume per ha. • • • • • Swath(Cms) WaterVolumeper haLt/min per(Ltr/ha) Nozzles

0.300 0.350 0.400 0.450 0.500 0.550 0.600

4 4 4 4 4 4 4

0.300 0.350 0.400 0.450 0.500 0.550 0.600

6 6 6 6 6 6 6

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Evaluate the discharge rate of nozzles (lit./min),Count the no. of nozzles Know the swath(cm) of the Drone at known height of spraying. Decide o nvolume (lit.)of spraysolution(water+pesticide formulation) to be sprayed

per ha. Work out the speed(m/s)of the Drone to be maintained during spraying. Calculate the time required to spray one acre 300 16

300 300 20 24

400 16

4.17

3.34 2.09 3.89 2.43 4.45 2.78 5.00 3.13 5.56 5.00 3.48 3.82 - 4.17 -

2.78 1.67 3.24 1.95 3.71 2.22 4.17 2.50 4.63 4.172.78 4.69 4.87 5.47 5.10 5.56 3.06 5.56 - 3.34 -

4.87 5.56 -

400 20 3.13 1.39 3.65 1.62 4.17 1.85 4.69 2.09 5.21 3.75 2.32 4.38 5.00 2.55 2.78 -

400500 24 16

500 20

500600 24 16

600 20

2.50

2.09

2.50

2.00

1.67

2.92

2.43

2.92

2.34

1.95

3.34

2.78

3.34

2.67

2.22

3.75

3.13

3.75

3.00

2.50

4.17 3.13 3.65 4.59 4.17 4.69 5.00 5.21 -

3.48 3.75 4.38 3.82 5.00 4.17 -

4.17 3.00 2.50 3.50 2.92 4.59 4.00 3.34 4.50 3.75 5.00 5.00 4.17 5.50 4.59 5.00

3.34 3.13 3.65 3.67 4.17 4.69 4.00 5.21 5.73 -

2.78 2.50 2.92 3.06 3.34 3.75 3.34 4.17 4.59 5.00

600 24

2.09 2.43 2.78 3.13 3.48 3.82 4.17

Crop Specific SOPs for Application of pesticide with drones Swath at different operational heights and spray angles of nozzles (a) Drone with boom sprayer

Theoretical coverage (b, meter) at different spray height (H, meter) Spray Angle

1.50

1.60

1.70

1.80

1.90

2.00

45

1.24

1.33

1.41

1.49

1.57

1.66

60

1.73

1.85

1.96

2.08

2.19

2.31

90

3.00

3.20

3.40

3.60

3.80

4.00

120

5.20

5.54

5.89

6.24

6.58

6.93

(Degree)

Crop Specific SOPs for Application of pesticide with drones

(b) Drone with nozzles below the propeller

Nozzle

Spray Angle (Degree)

N1

60-120

N2

60-90

N3

60-90

N4

60-120

Crop Specific SOPs for Application of Drones with Pesticides

Annexure-II Operational and safety requirements to ensure the safe, efficient and effective use of the inputs and the technology The following operational and safety measures need to be followed to ensure safe, efficient and effective use of the inputs and the drone technology Do's and Don'ts for pesticide application using drone

Do's

Don'ts

Before Application of chemical using drone Crop Parameters: The crop stage, height and canopy development should be taken into consideration before spraying using drone. The drone can be operated as per the crop condition for spot, band or elevated targeted spraying. For spot spraying the area should be marked first using appropriate marker. The drone spraying is most suitable for mono cropping pattern. Crop Field:Site parameters Check field comes under green, yellow or red zone.If field comes under yellow zone take proper permissions from DGCA and local police. Note down the Latitude and Longitude of the field for the record. Check GPS connectivity and stability status Check shape of the field whether drone can be used or not. The large crop field should be divided into small patches

Avoid chemical spray during pollination stage. Avoid using drone if crop is more susceptible to lodging. Avoid chemical spray using drone if rain is forecasted. Respect PHI of the crop

Do not plan for chemical spray using drone if field comes under red zone. Do not plan for chemical spray using drone nearby fodder crop, grazing field, water bodies like pond, river, canal etc., village, no crop field, roads, poultry house, barn yard,schools, etc. and maintain distance of 100m from these bodies. Do not plan for a large field spraying using drone to avoid risk of signal loss between remote control and the drone.

Crop Specific SOPs for Application of Drones with Pesticides for spraying using drone. Check terrain conditions (Slope, Plain or hilly). Check obstacles in the field like Trees, poles, HT line, Hill, power stations, solar systems, pumping station, fencing, agriculture machinery etc. Check Line of sight. Weather/Environment conditions: Note down the date and time for spraying on log book. Check the temperature and plan for spray if temperature is less than 35 °C. Check the humidity and plan for spray if humidity is more than 50 %. Check the wind speed and plan for spray if the wind speed is less than 8 km/h. Check the wind direction and according fix the starting home point of the drone for flying. Consider the weather forecastand take the decision accordingly for drone flying.Cloudy conditions would deter GPS connectivity Drone: Always have motor, propeller, ESC and battery in spare. Note down the drone type and payload capacity. The drone should be capable of flying in both Manual and Auto mode interchangeably. Calibrate the drone and ensure the good stability during operation. Check chemical feeder pipes to the nozzle for airlocks Ensure the nozzles are free from clogging and dry chemical flakes Ensure uniformity in discharge from each nozzle Check the GPS accuracy and decide the overlap percentage. Calibrate the RTK GPS based station if auto mode flying is planned. Check and calibrate the drone sensors like Lidar, --- etc. Optimise the range drone speed. Check remote control range and battery status. Check the Battery capacity and status and note down the battery age, number of battery etc. Check the drone

components for proper fitting. Check the drone propellers are in good condition. Check the drone motors are in good condition. Check the motor temperature. Ensure your drone (except Nano in uncontrolled airspace upto 50 feet) is Digital Sky “No Permission- No Take off" (NPNT) compliant. Obtain Unique Identification Number (UIN) from DGCA for operating in controlled airspace (where the ATC services are active) and affix it on your drone. Obtain Unmanned Aircraft Operator Permit (UAOP), if applicable from DGCA for commercial operations and keep it handy. Obtain permission before each flight through Digital Sky Platform which will be available on DGCA website from December 1. Keep an eye on interference which can be from mobile

Do not plan for chemical spray using drone if temperature is more than 35°C. Do not plan for chemical spray using drone if humidity is less than 50%. Do not plan for chemical spray using drone if wind speed is more than 8km/h. Do not plan for chemical spray using drone if the rain is expected within 4 hours.

Do not fly drone if battery are not in good condition and charged. Do not fly drone if propellers are broken or cracked. Do not fly drone if motor is heating too much Don’t fly a Nano drone above 50 feet from the ground level. Don’t fly a Micro drone above 200 feet from the ground level. Don’t fly drones more than 400 feet from the ground level. Don’t fly drone near other aircraft (manned or unmanned). Don’t fly drone near airports and heliports. Don’t fly drone over groups of people, public events, or stadiums full of people without permission. Don’t fly drone over government facilities/military bases or over/ near any no-drone zones. Don’t fly drone over private property unless permission is given. Don’t fly drone in controlled airspace near airports without filing flight plan or AAI/ADC permission (at least 24 hours before actual operation). Don’t drop or carry hazardous material. Don’t fly drone under the influence of drugs or alcohol. Don’t fly drone from a moving vehicle, ship or aircraft.

Crop Specific SOPs for Application of Drones with Pesticides devices or blockage of signals. Fly only during daylight (after sunrise to before sunset). Fly in good weather: Good weather lets you not only fly your drone better but also keep track of it when it is airborne. Fly in visual line of sight (VLOS): Always be within visual range of your drone. Be aware of airspace restrictions/ no drone zones and respect privacy of people. Keep local police informed about your drone flying activity. If you are ever approached by police provide all requisite information. Do log your flights and intimate concerned authorities (like DGCA, local police etc.) of any incidents/ accidents Spraying system Check the tank capacity and its cleniness Note down the pump flow rate capacity and set the pressure as per recommendation or as per mentioned in manual to operate the nozzle assembly Note down the number of nozzles and check the nozzles are not jam. Check the nozzles spacing and set as per the manufacturer manual. Note down the overall boom size of the sprayer. Check the nozzle discharge rate. Check the hose pipe and the connector for leakage. Check the leakage in the water tank and pipe line. Check the solenoid valve working and control through remote control. Check the tank is properly cleaned before filling the new chemical. Select right type and size of nozzles. Use separate sprayer for insecticides and weedicides. The droplet size for pesticide should in the range of 150 to 200 microns The droplet size for weedicide application should be in the range of 200 to 300 microns

Do not fly drone if the tank, nozzle, hose pipe are loose. Do not fill the chemical in the tank more than the recommended level. Do not fly drone if there is leakage in tank, hose pipe or connector. Do not fly drone if solenoid valve is not working properly. Do not fly drone if cap of the tank is missing. Do not fly drone if drone is unstable. Do not use leaky or defective equipment. Do not use defective/wornout and non- recommended nozzles. Do not blow/clean clogged nozzles with mouth.Instead use tooth brush tied with sprayer. Never use same sprayer for both weedicides and insecticides.

Chemical: Purchase pesticides/biopesticides only from registered pesticide dealers having valid License. Purchase only just required quantity of pesticides for single operation in a specified area. See approved labels on the containers/packets of pesticides. See Batch No., Registration Number, Date of Manufacture/ Expiry on the labels. Purchase pesticides well packed in containers.

Do not purchase pesticides from unregistered dealers or from un-licensed person. Do not purchase pesticide in bulk for whole season. Do not purchase pesticides without approved label on the containers. Never purchase expired pesticide. Do not purchase pesticides whose containers are leaking/loose/ unsealed.

During Storage:. Store the pesticides away from home premises Keep pesticides in original containers. Pesticides/weedicides must be stored separately. Where pesticides have been stored,area should be marked

with warning signs. Pesticides should be stored away from the reach of the children and live stocks. Storage place should be well protected from direct

Never store pesticide in home premises. Never transfer pesticides from original to another container. Do not store insecticides with weedicides. Ensure Crop protection chemicals are stored in lock and key Do not allow children to enter the storage place. Pesticides should not be exposed to sunlight or rain water.

Crop Specific SOPs for Application of Drones with Pesticides sunlight and rain. While handling: Keep pesticides separate during transportation Bulk pesticides should be carried tactfully to the site of application.

Never carry/transport pesticides along with food/fodder/other eatable articles. Never carry bulk pesticides on head, shoulder or on the back.

While preparing spray solution: Always use clean water. Use protective clothings viz., Nitrile hand gloves, face masks, cap, apron, full trouser, etc. to cover whole body. Always protect your nose, eyes, ears, hands, etc. from spill of spray solution. Read instructions on pesticide container label carefully before use. Prepare the solution as per requirement. Granular pesticides should be used as such. Avoid spilling of pesticides solutions while filling the spray tank. Always use recommended dosage of pesticide. No activities should be carried out which may affect your health.

Do not use muddy or stagnant water. Never prepare spray solution without wearing protective clothing. Do not allow the pesticide/its solution to fall on any body parts. v Never avoid reading instructions on container's label for use. Never use left out spray solution after 24 hours of its preparation. Do not mix granules with water. Do not smell the spray tank. Do not use overdose which may affect plant health and environment. Do not eat, drink, smoke or chew during whole operation of pesticides.

While applying spray solutions Crop and site specific Mark the boundary corners of the crop field using flag or mirrors. Check if any other drone operator is flying the drone nearby fields. Drone operation Keep eye on drone stability during operation. Keep drone with in the visible range. Take care of obstacles in the crop field. Take care of overlap percentage of swath. Take care drone is flying with in the periphery of crop field. Drone should have emergency landing option during battery discharge Keep spare charged batteries for emergency. Sprayer control Apply only recommended dose and dilution. Spray operation should be conducted on cool and calm day. Spray operation should be conducted on sunny day in general. Use recommended spraying combination for each mission Spray operation should be conducted in the wind direction. After spray operation, sprayer assembly and other equipment used during the operation should be washed with clean water using detergent/soap.

Do not fly drone without marking boundary corner of the crop field. Do not fly drone very close to the crop canopy. It may cause crop lodging. Animals should not be allowed to enter into the field during operation. Drone operator should not hand over the control of drone to other unskilled person during operation Do not fly the drone very close to obstacle points. Do not fly drone out of the visible range. Do not fly drone if it is unstable. Do not keep overlap percentage more than --- percentage or less than ----- percentage. Do not spray if the nozzles are jammed. Do not allow drone to enter another crop field.

Never apply over-dose and high concentrations than recommended. Do not spray on hot sunny day or strong windy conditions. Do not spray just before rains and immediately after the rains. Do not spray against wind direction. Containers and buckets used for mixing pesticides should never be used for domestic purpose even after thorough washing. Never enter in the treated field immediate after spray without bearing protective clothing

Crop Specific SOPs for Application of Drones with Pesticides Drone operator and accidents Drone operator must wear the PPEs during spraying operation Remote control should be in hand of the operation even if the drone is in auto mode. Drone operator should cover his eyes with goggles to avoid chemical exposure. Drone operator should inform to local police if drone crashed accidently and it should recoded in log book with proper reason of accidents. Take also the photographs of the accident. Operator has to apply for insurance claim as soon as possible.

. Drone operator should not remove the PPEs during spraying operation Drone operator should not remove safety goggles during operation. Drone operator should not stand in the direction of the wind to avoid chemical exposure due to drift. Drone operator should not allow other person to stay very near the drone take-off and landing point.

After Spray Operation: General Avoid the entry of animals/workers in the field immediately after spray. Drone Take out the battery from the drone and put for charging immediately. Check the motor temperature and propellers. Clean the chemical exposed surfaces of the drone. All the accessories of drone should be kept intransportation box/bag. Sprayer and chemicals The used/empty containers should be triple rinsed, dried and punctured and handed over to disposal agency Left over spray solutions should be disposed off at safer place viz. barren isolated area. Drone Operator Clean the PPE after use Wash hands and face with clean water and soap before eating/smoking. On observing poisoning symptoms give the first aid and show the patient to doctor. Also show the empty container to doctor.

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Do not irrigate the field just after spraying of chemicals Do not harvest the crop just after spraying for fodder. Do not spray the fertilizer just after chemical spray Do not expose the battery terminal point to avoid short circuiting. Do not forget the drone and its accessories in the field after spraying

Empty containers of pesticides should not be re-used for storing other articles. Left over spray solution should not be drained in or near ponds or water lines etc.

Never eat/smoke before washing clothes and taking bath. Do not take the risk by not showing the poisoning symptoms to doctor as it may endanger the life of the patient

Crop Specific SOPs for Application of Drones with Pesticides

Annexure-III Suggested Proforma for collection of information for developing crop specific SOP by different institution during drone assisted pesticide application experiment As the experimental data was available for only nine crops, therefore, committee developed SOPs for those nine crops only. There is a need to generate data on remaining crops for development of SOPs . The committee also prepared a proforma for information collection during assisted spraying experiment.

Note: The proforma may be filled for each spraying operation and for each crop separately. Incase replicated data then use single sheet with one replication each coloumn 1. Experimental Site Details i. Location (Latitude, Longitude, Altitude) ii. Approximate distance of nearest obstacle (tree, pole, wall, building etc) from the starting point of drone (m) iii. Shape of each plot iv. Total area covered during the experiment 2. Crop and Chemical Information i. Name of the Crop ii. Crop Variety iii. Crop spacing (between rows x between plants): iv. Crop height at the time of spraying: v. Growth stage of crop vi. Name of the target disease /pest vii. Name of the pesticide viii. Type of formulation: ix. Concentration (g ai/lit or % or ml/L) x. Dosage (g/ha or ml/ha) xi. Dosage selection method (Recommended/ Trial based) 3. Environmental Conditions of the Experimental Site i. Temperature (0C) ii. Wind velocity(km/h) iii. Relative humidity (%) iv. Wind direction (degrees from N) 4. Drone Details i. Payload (kg) ii. Maximum take-off weight (kg) iii. Drone Type: Small/ Medium/ Large iv. Drone category: Multi-copter, Hybrid, others v. Power Source (Battery/fuel/hybrid) vi. Battery storage (mAh), if battery powered: vii. Fuel type if fuel operated 5. Spraying System Details Maximum tank capacity

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R1

R2

R3

Crop Specific SOPs for Application of Drones with Pesticides Tank material Maximum volume filled at the start of experiment: Type of nozzle No.of nozzles 6. i. ii. iii. iv. v. vi.

Operational Parameters Height above crop canopy Operating pressure of spraying sytem Nozzle flow rate (lit/ min) Flying speed (m/sec) Flying direction (degrees from N) Spraying type (a) Uniform (b) Variable rate spraying vii. if variable rate spraying, then variations a. In spatial scale and /or b. Spray rate viii. How the decision is made for site specific spray and rate of spray (a) based on crop health monitoring (i) infections levels and (ii) abiotic stress-nutrient stress levels (b) Source of crop health data (i) from ground collected

information, eye estimate (ii) from drone based surveillance 7. Performance Parameters i. Droplet size range (µm) ii. VMD iii. NMD iv. Coefficient of Uniformity (%) v. Spray width (m) vi. Overlap (%) vii. Bio-efficacy/ mortality viii. Please mention ix. Time after treatment (hours) & x. Method of efficacy/mortality estimation xi. Theoretical field capacity xii. Actual field capacity xiii. Major time losses xiv. Battery operational time xv. No. of tank fillings per hectare 8. Other details Any major breakdown during the experiment Any major observation during the experiment Any adverse effect on non-target organism or crop

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Crop Specific SOPs for Application of Drones with Pesticides

Proforma used for collection of Information

Government of India Ministry of Agriculture and Farmers' Welfare Department of Agriculture, Co-operation and Farmers' Welfare (Mechanization and Technical Division) The proforma for providing the information required for developing the crop specific Standard Operating Procedure (SOP) for application of Drones with Pesticide and Crop Nutrient Spraying Notes: 1. This proforma has been developed by a committee constituted for the preparation of the draft for the crop specific Standard Operating Procedure (SOP) for application of Drones - with Pesticide and Crop Nutrient Spraying vide Ministry Order No. F 13-10/2022 M&T (I&P) dated 26th July 2022 2. The proforma consists of the exhaustive list of the parameters required for developing the SOPs. 3. In case of the observations have already been taken,provide the information on parameters (as maximum as possible) 4. In case of the planned drone spraying operations, plan the operations in such a way that the maximum parameters listed in this proforma are recorded. 5. This proforma is for only one spraying operation for a specified crop. In case of more than one spraying during crop growth period (say for different crop growth stages or incidences of pest and disease as observed), use this proforma separately for each operation (if the same drone/spraying system is used for different operations during crop growth stage, details in Tables 1, 3 and 4 can be copied for these operations)

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Crop Specific SOPs for Application of Drones with Pesticides

Name of the Organization (SAUs, KVKs, ICAR Institutes, FPOsetc) /Individual (farmer, drone service provider etc): Date of drone spraying: Table 1. Location details Sr. No.

Parameters

1

Village/town, Tehsil, District, State

2

Latitude and Longitude

3

Altitude (m)

4

Surrounding (sea shore/ flat lands/ forest/ hills)

Details

Table 2. Crop details Sr. No.

Parameters

1

Crop name

2

Variety/Hybrid

3

Type (rainfed/irrigated)

4

Spacing (row (m) x plant (m))/ Plant population (No/ha)

5

Date of sowing

6

Stage of crop (as on date of spraying)

7

Shaded area (%, if measured OR fully, partly, sparsely based on eye observations) (as on date of spraying)

Details

Table 3. Drone details (as per specifications) Sr. No.

Parameters

1

Classification (Small/Medium/Large)

2

Category (Multi-rotor/Hybrid) and No. of rotors

3

Maximum take-off weight (kg)

4

Power source (battery/fuel) In case of battery, provide capacity in mAh In case fuel, provide type

5

Other standard specifications of the drone model used

Details

Crop Specific SOPs for Application of Drones with Pesticides for spraying from Manufacturers (control range, endurance, flight time, controller, fail safe features, etc…) (Provide these specifications here or on separate sheet) 6

Photographs of the drone model used for spraying (provide here or attach separately)

Table 4. Spraying system details Sr. No.

Parameters

1

Tank capacity (lit)

2

Nozzle mounting (on boom/below propeller)

3

Length of boom (for boom mounted) (m)

4

No. of nozzles

5

Type of nozzle

6

Cone Angle

7

Drop let size (µm)

8

Discharge/Flow rate through nozzle (lit/min)

9

Operating Pressure (Kg/cm2)

Details

• Formulations sprayed (use appropriate table) Table 5 (A). Pesticides (chemical/bio-pesticides) Sr. No.

Parameters

1

Target disease/pest

2

Type of formulation

3

Name of pesticide

4

Concentration (g ai/lit or % or ml/ for chemical and ml/Lit for bio-formulations

5

Dosage (g/ha or ml/ha)

6

Water volume (lit/ha)

Details

Table 5 (B). Crop nutrients (chemical nutrients/bio-fertilizers) Sr. No.

Parameters

1

Target deficiency

2

Type of formulation

3

Name of crop nutrient

Details

Crop Specific SOPs for Application of Drones with Pesticides 4

Type of nutrient (nano/micro/macro)

5

Concentration (g ai/lit or % or ml/ for chemical and ml/Lit for bio-formulations

6

Dosage (g/ha or ml/ha)

7

Water volume (lit/ha)

- Observations Table 6(A) Environment Sr. No.

Parameters

1

Temperature (oC)

2

Relative humidity (%)

3

Wind speed (km/hr) and direction

Details

Table 6(B) Drone operating parameters Sr. No.

Parameters

1

Flight modes (Manual/Autonomous/A-B mode)

2

Flying speed (m/s)

3

Height above canopy (m)

4

Swath (m)

5

Overlap (%)

6

Spray width (m)

7

Spray flow (lit/min)

8

Flight direction (Windward side/Leeward side)

9

Time of spray (start and end)

10

Total area covered (ha)

11

Total flight time (spraying time i.e. between drone takeoff to drone landing) required to cover the area, min

12

In case of multiple flights, provide area covered and flight time for each flight

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Details

Flight No.

Area (ha)

Time (min)

Crop Specific SOPs for Application of Drones with Pesticides

Table 6(c) Drone operating parameters Sr. No.

Parameters

1

Field capacity- Theoretical (ha/hr)

2

Field capacity- Actual (ha/hr)

3

Spray Parameters (based on observations with water sensitive papers). Provide averages if recorded as top, muddle and lower canopy and on windward, crop and leeward sides and details to be provided in separate tables (a) Volume Median Diameter-VMD (µm) (b) Number Median Diameter-NMD (µm) (c) Droplet density (No./cm2) (d) Spray uniformity (%)

4

Control efficiency (%)

5

Phyto-toxicity observations/effects

6

Efficacy

7

Other observations

- Other related information

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Details

Crop Specific SOPs for Application of Drones with Pesticides

Annexure-IV: Instructions to be adhered to by the drone operators

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Crop Specific SOPs for Application of Drones with Pesticides

Special thanks for providing information 1.

Professor Jayashankar Telangana State Agricultural University, Rajendranagar, Hyderabad, Telangana 2. Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu

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Source: `Inviting-Comments-on-Draft-SOPs-merged.pdf` · Google Drive file id `1yptl-oKiV575EKOal0nN2vfQJdcLoPF5` · folder "8. Agricultural University Research"

Ministry-of-agriculture

12/22/21, 8:26 PM

Ministry of Agriculture & Farmers Welfare

Union Agriculture Minister releases Standard Operating Procedure (SOP) for use of Drone in Pesticide Application for Crop Protection and for spraying Soil and Crop Nutrients Drone Technology is useful for Agriculture and will benefit Farmers: Shri Narendra Singh Tomar Posted On: 21 DEC 2021 5:48PM by PIB Delhi

The adoption of drone technology is the need of the times and will benefit farmers. Stating this during the release of Standard Operating Procedures (SOPs) for drone application in Agriculture, the Union Minister Shri Narendra Singh Tomar said that under the leadership of Prime Minister Modi all policies since 2014 are aimed at doubling farmer's income by 2022. He said that the formation of Farmer Producer Organisation (FPOs) and the Agriculture Infrastructure Fund (AIF) will bring about a revolution in the lives of small farmers. The Minister informed that the drones were used for the first time in warding off the locust attacks in various states of the country. He said that the government is making continuous efforts to infuse new technologies in agriculture so as to provide sustainable solution in context of enhancing the productivity as well as efficiency of the agriculture sector. The SOP for drone regulation for pesticide application covers important aspects like statutory provisions, flying permissions, area distance restrictions, weight classification, overcrowded areas restriction, drone registration, safety insurance, piloting certification, operation plan, air flight zones, weather conditions, SOPs for pre, post and during operation, emergency handling plan.

Considering the unique advantages of Drone technologies in agriculture, the Ministry of Agriculture & Farmers Welfare, (Department of Agriculture & Farmers Welfare) in consultation with all the stakeholders of this sector, has brought out Standard Operating Procedures (SOPs) for use of drones in pesticide and nutrient application that provides concise instructions for effective and safe operations of drones. The use of Unmanned Aerial Vehicles (UAVs) commonly known as drones have great potential to revolutionize Indian agriculture and ensure country's food security. The National drone policy has been notified and the Drone Rules 2021 have been made significantly easier for people and companies in the country to now own and operate drones. The requisite fees for permissions have also been reduced to nominal levels. Drones are well-equipped with many features like multi-spectral and photo cameras and can be used in many areas of agriculture sector such as monitoring crop stress, plant growth, predict yields, deliver props like herbicides, fertilizer and water. Drones can be used for assessing the health of any vegetation or crop, field areas inflicted by weeds, infections and pests and based on this assessment, the exact amounts of chemicals needed to fight these infestations can be applied thereby optimizing the overall cost for the farmer. Drone planting systems have also been developed by many start-ups which allow drones to shoot pods, their seeds and spray vital nutrients into the soil. Thus, this technology increases consistency and efficiency of crop management, besides reducing the cost. The farmers face many problems like unavailability or high cost of labours, health problems by coming in contact with chemicals (fertilizers, pesticides, etc.) while applying them in the field, bite by insects or animals, etc. In this context, drones can help farmers in avoiding these troubles in conjunction with the benefits of being a green technology. Use of drones in agriculture may also give ample opportunities to provide employment to people in rural areas. During the release of SOPs event in the Agriculture Ministry, Secretary Agriculture Shri Sanjay Agarwal delivered an address on advantages of drone technologies. Others who witnessed the event were Minister of State for Agriculture Shri Kailash Choudhary and Ms. Shobha Karandlaje. Senior

officials of the ICAR, State government officials and owners of the Custom Hiring Centres all across the country witnessed this event through webcast. Click here for detailed SOPs

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APS (Release ID: 1783937) Visitor Counter : 1848

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NBAIR-Drone demonstration for NBAIR website final 0

ICAR-NBAIR Demonstrated Utility of Agri-drone in Crop protection ICAR- National Bureau of Agricultural Insect Resources, Bengaluru has been making efforts to develop novel and precise delivery mechanism for biopesticides for the effective management of insect pest and diseases. Further, ICAR-NBAIR has been selected as one of the ICAR Institutes for "Drone technology demonstration" under the Sub Mission on Agricultural Mechanization to popularize the Agri-drone among farming communities. In this direction ICAR-NBAIR conducted about

15

biopesticides

spraying

demonstrations in three clusters (5 demonstration /cluster) using oil based formulation in Tumkuru and Chikkamagaluru

districts

of

Karnataka

Tiruppur

and

and

Coimbatore districts of Tamil Nadu in different crops such as coconut, brinjal, mango, sugarcane, arecanut and rice to create farmers' awareness and promotion of drone technology especially in crop protection. These demonstration programs were attended by about 500 progressive farmers, line department officials, farmers producing organization (FPOs) officials, women shelf help groups (SHGs), custom hiring centers (CHCs) and other stakeholders which created great interest and motivation. During demonstration, it was briefed about various government subsidy schemes for procurement of agri-drone to different target groups like government institutions, ICAR-KVKs,

Line

departments,

FPOs,

SHGs and CHCs. The drone technology is a revolutionary technology that is effectively used for the precision spraying of pesticides, thereby reducing chemical usage and its cost of applications, assessment of crop health, and real-time monitoring of pest, disease and weed over large area thus enabling timely action on management strategies.

Drone-based pesticide spraying is also safer for farmers avoiding physical exposure to pesticides and is more convenient to some inaccessible cropping system like sugarcane, uneven terrain like tea and coffee plantation and taller crops like coconut and arecanut, where manual spraying is challenging. Crop-spraying drones have much higher work efficiency (7-8 minutes /acre) as compared to manual spraying.

Moreover, manual spraying leads to non-uniform biopesticide application, poor penetration of active ingredient into the dense canopy and low application efficiency leading to inadequate control of pests and diseases. Therefore, ICAR-NBAIR is working on development of standard operating procedure (SOP) for bio pesticide application viz., dosages, efficacy on target insect pest;drift effect and particle size etc. Use of biopesticides through drone has led to a greater bio-suppression of pests.

ICAR-NBAIR, acknowledges Keladi Shivappa Nayaka University of Agricultural and Horticultural Sciences, Shivamogga, Zonal Agricultural & Horticultural Research Station, Bavikere, Chikkamagaluru and Demonstration-cum-Seed Production (DSP) Farm of Coconut Development Board, Udumalpet, Tiruppur for facilitating for the demonstration.

These entire demonstration

programmes widely covered in print and media in regional languages for the benefit of different stakeholders.

Source: The Director, ICAR-National Bureau of Agricultural Resources, Bengaluru

Source: `NBAIR-Drone demonstration for NBAIR website final _0.pdf` · Google Drive file id `1uFhC16zup7mE_fl9JdQtVFFnESxbgxMp` · folder “8. Agricultural University Research”

Success-story-3

Success Story Empowering Rural Women through Drone Technology Name of the Enterprise / Crop: Farm mechanization Name of the Farmer: Mrs. Rohini Pankaj Shinde (First “Drone Didi” of Latur District) Address: At Post. Gangapur, Tq. & Dist. Latur, Maharashtra- 413 531 1. Situation Analysis / Problem Statement Gangapur village of Latur district is located in a drought-prone region of Marathwada characterized by erratic rainfall, frequent dry spells, and limited irrigation resources. The major crops grown in the area include soybean, chickpea, pigeon pea, sorghum, safflower, maize, sugarcane (in irrigated pockets), vegetables, flowers, and mango orchards. Crop productivity in the region largely depends on timely plant protection measures. However, farmers in the village were facing serious constraints in plant protection management. Acute labour scarcity during peak spraying periods resulted in delayed pesticide application. Traditional knapsack sprayers were labour-intensive and required large volumes of water (200–250 liters per hectare). Spray coverage was often uneven, especially in tall crops such as sugarcane and pigeon pea. Farmers were directly exposed to harmful chemicals, causing health concerns. Due to improper and delayed spraying, pest and disease incidence in soybean and chickpea led to yield losses of 10–25 percent in several cases. Women in agriculture were mainly engaged in manual farm operations and had limited access to advanced agricultural machinery. There were very few income diversification opportunities for rural women, and no structured drone-based custom hiring services were available in Latur district at that time. Despite these constraints, the district had strong institutional support and progressive farmers willing to adopt innovative technologies. Recognizing the need for precision agriculture and women empowerment, KVK, Latur initiated efforts to introduce drone-based pesticide spraying technology in the region. 2. Plan, Implementation and Support To address the identified problems, Krishi Vigyan Kendra, Latur initiated On-Farm Trials (OFTs) on drone spraying technology in soybean and chickpea crops. The objective was to evaluate its efficiency, spray uniformity, reduction in chemical consumption, and economic feasibility under local conditions. The trials demonstrated that drone spraying required only 20–25 liters of spray solution per hectare and achieved uniform droplet distribution with high field efficiency (1.5–2.0 hectares per hour). The technology significantly reduced operator exposure to pesticides and ensured timely plant protection. Mrs. Rohini Pankaj Shinde from Gangapur actively participated

in these demonstrations and training programmes. She underwent structured skill training conducted by KVK, which included drone

operation, calibration, safety protocols, battery management, pesticide handling, minor troubleshooting and business planning for custom hiring services. Farmer–scientist interactions, field demonstrations and exposure visits further enhanced her confidence and technical competence. With technical guidance from KVK, she applied under the Government of India's Drone Didi Scheme and successfully procured an agricultural spraying drone. KVK provided continuous advisory services and field-level support during the initial phase of operation. With this initiative, she became the first "Drone Didi" of Latur district, marking a significant milestone in women-led agricultural mechanization in the region. 3. Output After procuring the drone, Mrs. Rohini Shinde started providing custom hiring services for pesticide spraying across various crops in Gangapur and neighboring villages. During the operational year, she covered a total spraying area of 810 acres. She sprayed 185 acres of sugarcane at a rate of ₹700 per acre, generating ₹1,29,500. In soybean, she covered 150 acres at ₹500 per acre, earning ₹75,000. Chickpea spraying was conducted on 175 acres, generating ₹87,500. Safflower was sprayed on 127 acres with an income of ₹63,500. Additional crops included sorghum (5 acres), green gram, black gram and pigeon pea (50 acres), maize (20 acres), flowers (15 acres), tomato (65 acres), and mango orchards (18 acres at ₹1000 per acre). Through these operations, she generated a total income of ₹4,51,000 from 810 acres of spraying services. The introduction of drone technology resulted in several immediate outputs. Farmers experienced 25–30 percent reduction in chemical usage due to low-volume precision spraying. Labour requirements were reduced by nearly 40–50 percent. Timely spraying improved pest and disease management, leading to better crop protection. Mrs. Rohini significantly enhanced her technical skills, entrepreneurial capacity, and digital agriculture knowledge. Sr. No.

Crop

Spraying Area,

Spraying Rate per

Acre

Acre

Total Income

1.

Sugarcane

185

700/-

129500/-

2.

Soybean

150

500/-

75000/-

3.

Chickpea

175

500/-

87500/-

4.

Safflower

127

500/-

63500/-

5.

Sorghum

05

500/-

2500/-

6.

50

500/-

25000/-

7.

Green gram, Black gram and Pigeon Pea Maize

20

500/-

10000/-

8.

Flowers

15

500/-

7500/-

9.

Tomato

65

500/-

32500/-

10.

Mango

18

1000/-

18000/-

810

--

451000/-

Total

- Outcome The success of drone spraying services created a positive ripple effect in the surrounding villages. Farmers from neighboring villages began availing her services, leading to horizontal spread of the technology. More than 550 farmers benefitted directly from drone spraying services in a single year. Farmers reported improved crop health and yield stability due to timely and uniform spraying. On average, yield improvement and cost savings together provided an estimated additional benefit of approximately ₹1,500 per acre. For 810 acres, this translated into an indirect economic benefit of nearly ₹12,15,000 to the farming community. The technology also reduced excessive pesticide application, thereby minimizing

environmental contamination and improving soil and water quality. Reduced human exposure to chemicals improved occupational safety. From a women empowerment perspective, Mrs. Rohini Shinde emerged as a role model for rural women and Self-Help Groups. Her increased income improved the financial stability of her family and strengthened her decision-making role within the household and community. 5. Impact At the district level, the initiative contributed to the promotion of precision agriculture and digital farming practices in Latur. Drone spraying gained visibility as a viable alternative to conventional plant protection methods. The custom hiring model demonstrated by Mrs. Rohini created a sustainable rural service enterprise. Economically, her enterprise generated ₹4.51 lakh annual income and stimulated the rural service economy. Indirect benefits to farmers strengthened the agricultural economy of the area. Socially, her recognition as the first Drone Didi of Latur district enhanced the status of women in mechanized agriculture. Her success improved household living standards and educational opportunities for her children. Institutionally, KVK, Latur strengthened its role as a technology incubation and extension center by successfully promoting drone-based precision agriculture. The model demonstrated effective convergence of government schemes, institutional support, and grassroots entrepreneurship. Environmentally, the technology promoted climate-smart agriculture by ensuring timely spraying during narrow weather windows, reducing chemical load, and improving resource-use efficiency in drought-prone conditions. Conclusion The journey of Mrs. Rohini Pankaj Shinde from a rural woman farmer to the first Drone Didi of Latur district reflects the transformative potential of agricultural mechanization combined with institutional support. Through strategic intervention by Krishi Vigyan Kendra, Latur, she adopted advanced drone technology, generated substantial income, provided precision spraying services across 810 acres, and delivered measurable economic and environmental benefits to the farming community.

Photographs

Active participation of Mrs. Rohini Shinde in skill development training on precision agriculture technologies.

Practical session on drone calibration and safe pesticide handling during training programme.

Certificate distribution ceremony after successful completion of Training at KVK, Latur.

Drone Didi Scheme beneficiary Mrs. Rohini Shinde with her agricultural spraying drone unit.

Mrs. Rohini Pankaj Shinde operating agricultural drone for spraying

Mrs. Rohini Pankaj Shinde operating agricultural drone for spraying in sugarcane and soybean field.

Source: `Success-story-3.pdf` · Google Drive file id `1DP1suwVMSpSghmYiEzBCXRVgQ22l8gsG` · folder “8. Agricultural University Research”

TeeJet Performance Result

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TECHNICAL ARTICLE

Evaluation of Spray Characteristics of Pesticide Injection System in Agricultural Drones Seung-Hwa Yu 1 & Young-Keun Kim 1 & Hyeon-Jong Jun 1 & Il Su Choi 1 & Jea-Keun Woo 1 & Young-Hwa Kim 1 & Young-Tae Yun 1 & Yong Choi 1 & Reza Alidoost 2 & Jeekeun Lee 2 Received: 29 July 2020 / Revised: 22 September 2020 / Accepted: 23 September 2020 # The Korean Society for Agricultural Machinery 2020

Abstract Purpose This study aims to verify that the characteristics of the typical injection pumps and nozzles used in pesticide injection systems in current agricultural drones in Korea are consistent with those presented in the product specifications, and to provide experimental quantitative data for selecting the correct pump and nozzle. Methods The performances of three types of pumps and 18 types of nozzles currently in use were evaluated in terms of the pressure-flow rate curve, injection flow rate, spray angle, and droplet size. Results For pesticide injection pumps, the maximum pressure and pressure-flow rate curve should include the nozzle’s injection pressure and flow rate range. Most of the 18 nozzles used in the test showed nearly the same results as the flow rates suggested from the manufacturer, but the spray angle showed a difference of up to 10%. The droplet size was slightly smaller than the value suggested by the manufacturer, and the relative span factor ranged from 0.2 to 1.2. Conclusion The pressure-flow rate curves of the injection pumps and spray angles of the

commercial nozzles used for agricultural control drones must be evaluated for official approval/assessment of such agricultural drones to ensure the performance of agricultural drone sprayers. Keywords Agricultural drone sprayer . Injection nozzle . Pesticide injection system . Precision pesticide control

Introduction Recently, owing to developments in science and technology, the mechanization and “intelligentization” of agriculture have been rapidly progressing, and farming using unmanned helicopters and drones is emerging as a countermeasure for the aging agricultural labor population. Agricultural drones are being used to observe diseases and pests such as pine wilt, as well as for precision pest control, such as by spraying pesticides. Precision pest control using drones is known to have a high control *Young-Tae Yun yush6210@korea.kr* Jeekeun Lee leejk@jbnu.ac.kr 1

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2

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effect, as the low altitude (3 to 5 m) for spraying pesticides minimizes the exposure to pesticides, and the downward wind from the drone rotor blade allows the pesticides to evenly permeate to the lower parts of crops. Moreover, it is attracting significant attention from farmers, as the average control time is 1/10 that of power sprayers, saving labor. Moreover, it is very economical, with 1/5 of the purchase cost and 1/10 of the operation cost of unmanned helicopters. In addition, it can solve problems related to the usage of burst sprayers and manned helicopters, such as the low pest control efficiency caused by the scattering of the pesticides in the air (Yeom and Jung 2019; Jung et al. 2015). Although agricultural drones are widely used in pest control, the nozzles for conventional power sprays or unmanned helicopters are still being used in the pesticide injection systems mounted on drones, without sufficient review of the flight characteristics and operating environments. In particular, as the rotor blade downward wind flow of agricultural drones is different from that of unmanned helicopters owing to the characteristics of lift and thrust generated by the

multirotor blades, it is necessary to optimize the design of the pesticide spray system while considering the downward wind (Choi et al. 2019; Shukla and Komerath 2018; Qing et al. 2017). An agricultural drone for pest control consists of a flying body and pesticide injection system mounted on the drone (Myint and Kim 2019). The pesticide injection system for an agricultural drone consists of a pesticide tank, controller, pesticide pump, DC motor, spray boom, tube, and nozzle. The variables influencing the pest control effect include the rotor blade downward wind flow characteristics, pesticide injection flow rate, injection pressure, injection speed, number of nozzles, location of installation, nozzle structure, and nozzle spray characteristics (speed and droplet size). Therefore, it is necessary to optimize many variables to improve the application rate through precision pest control, and to improve the pest control efficiency by reducing spray drift potential. Many studies related to agricultural drones have been conducted, and several research groups are currently conducting research in various fields related to the optimization of pest control systems with drones. However, most studies related to agricultural drones focus on the drone body in the performance of a specific task, such as in-flight attitude control, communication, collision avoidance, or optimization of the path for the pest control mission (Pharne et al. 2018; Reddy et al. 2017; Maguteeswaran and Srinivasan 2016). There are relatively few studies related to the pesticide injection systems in agricultural drones and nozzle optimization technology. In South Korea, studies have been conducted on pest surveillance using drones (Lee et al. 2017) and on the spray drift characteristics in the aerial application (Jin et al. 2008; Park et al. 2007; Kim et al. 2019a, b), but there are not many studies addressing the pesticide spray nozzles in the pest control systems of agricultural drones. In particular, most of the agricultural drone sprayers used in Korea are made by smalland medium-sized businesses that imitate Chinese products, and the significance of this study is that there is no data to be used for reference. Therefore, this study aims to verify whether the characteristics of typical spray pumps and nozzles for the pesticide spray systems of agricultural drones currently used in South Korea are consistent with those suggested in the product specifications. In addition, it aims to induce the selection of the proper pumps and nozzles by providing experimentally proven quantitative data. To this end, the performances of three types of pumps and 18 types of nozzles currently in use were evaluated in terms of the

pressure-flow rate (P-Q) curve, injection flow rate, spray angle, and droplet size all of which affect the efficiency of drone sprayers.

Materials and Methods Test Pump and Nozzles The Ministry of Agriculture, Food, and Rural Affairs enacted and published the “Inspection Methods and Criteria for Agricultural Spraying Drones” in June 2016 to promote the agricultural use of drones (KS 2016). The criteria for pesticide injection systems installed in agricultural drones are described in detail in “Table 4: Agricultural Machinery Inspection Methods, (77) Agricultural Spraying Drones” and “Table 5: Agricultural Machinery Inspection Criteria, (66) Agricultural Spraying Drones.” One pesticide spray nozzle-related item among the inspection criteria for agricultural drones states that agricultural drones should meet a spray rate of 8 L/ha ± 15% per area. This inspection criterion was prepared from the viewpoint that a pesticide should be applied in the amount required for the target, in terms of the pest control effect. To satisfy this criterion, the pest control speed (according to the number of nozzles mounted on the drone), the injection flow rate per nozzle, and pesticide spraying width must be determined. Based on the 8 L/ha suggestion in the criteria for agricultural drones, the required spraying length changes from 2333 to 1429 m when the spraying width changes from 3 to 7 m. When the spraying speed is set to 2 to 5 m/s, the required spraying time is 28 to 5 min, and the injection flow rate is in the range of 0.29 to 1.68 liters per minute (LPM). Considering the spraying width (5 m) and spraying speed (3 m/s) most commonly used in domestic agricultural drones, the total injection flow rate of the nozzles mounted on an agricultural drone is set as 0.8 L/min, and the average flight time for spraying an area of 1 ha is approximately 10 min. This standard is similar to the Japanese standard (ISO/DIS 16119-5 (2018): Environmental Requirements for Sprayers - Part 5: Aerial Spray Systems), which is defined by an 8 L/ha uniform spraying and 6% error range at a spraying rate of 0.8 L/min (ISO/DIS 16119-5 (2018)). Most of the nozzles used in the pesticide spray systems of domestic agricultural drones are XR series (flat fan) nozzles. Some nozzles are equipped with TP series (cone jet) nozzles, with an injection flow rate in the range of 0.25 to 0.76 LPM (0.068 to 0.2 gallons per minute (GPM)). Table 1 shows the nozzles currently used in agricultural control drones, and similar nozzles for comparison; a total of 18 nozzles from four series (XR, TP, TX, and AI) were used for the performance evaluation. As it is important for agricultural drones to spray pesticide to as many areas as possible within a limited flight time by using the electric energy charged in the battery, it is efficient to fly with a large battery and as much pesticide as possible. Therefore, a lighter takeoff weight of the flying vehicle allows for a larger load of pesticide, and the capacity of the pesticide injection pump mounted on the drone should be optimized for the injection conditions. The pesticide injection pump

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List of test nozzles with classified into four groups (XR, TX, TP, AI series)

Nozzle

Flow rate @ 2.76 bar (40 psi)

Spray angle

Operating pressure

Series

Name

Type

Gallons per minute (GPM)

Liters per minute (LPM)

degree

psi

bar

XRa)

XR8001-VS XR80015-VS XR80020-VS XR11001-VS

Flat fan Flat fan Flat fan Flat fan

0.10 0.15 0.20 0.10

0.38 0.57 0.76 0.38

80 80 110 110

15–60 15–60 15–60 15–60

1.03–4.14 1.03–4.14 1.03–4.14 1.03–4.14

XR110015-VS XR110020-VS TX VK-04 TX VK-06 TX VK-08 TX VK-12 TP8001-VS TP11001-VS TP8002-VS TP11002-VS TP800067-VS TP1100067-VS AI110015 AI11002

Flat fan Flat fan Hollow cone Hollow cone Hollow cone Hollow cone Flat fan Flat fan Flat fan Flat fan Flat fan Flat fan Flat fan Flat fan

0.15 0.20 0.067 0.10 0.133 0.20 0.10 0.10 0.20 0.20 0.067 0.067 0.15 0.20

0.57 0.76 0.25 0.38 0.50 0.76 0.38 0.38 0.76 0.76 0.25 0.25 0.57 0.76

110 110 80 80 80 80 80 110 80 110 80 110 110 110

15–60 15–60 30–300 30–300 30–300 30–300 30–60 30–60 30–60 30–60 30–60 30–60 30–100 30–100

1.03–4.14 1.03–4.14 2.07–20 2.07–20 2.07–20 2.07–20 2.07–4.14 2.07–4.14 2.07–4.14 2.07–4.14 2.07–4.14 2.07–4.14 2.07–6.9 2.07–6.9

TXb)

TPc)

AId)

a), b), c), d) series (Spraying system Co. Ltd., Glendale Heights, IL, USA). Schematics and specifications of all nozzle listed in this table can be found in Spraying system Co. Ltd

currently used is equipped with a DC motor and uses the pulse width modulation (PWM) or voltage control to control the number of revolutions. In this study, three models were selected for investigating the performance of the pesticide injection pumps mounted on agricultural drones. The three pumps used in this study were selected by referring to agricultural control drones used in Korea. Table 2 shows the types and specifications of the pumps used in the experiment.

Measurement of Flow Rate and Spray Angle The experimental apparatus shown in Fig. 1 was constructed to evaluate the performance of a pesticide spray system in an agricultural control drone. The experimental apparatus consisted of a liquid supply unit, pesticide spray pump and Table 2

spray nozzle, spray image acquisition device, droplet size measuring device, and control system. The device for evaluating the P-Q characteristics of the pesticide injection pump and measuring the injection flow rate of the nozzle consisted of a liquid supply device, volumetric flow meter (Model IOG 1/4″, flow range: 0.44–8.3 LPM, Badgermeter, Neuffen, Germany), and pressure measurement sensor (ETM-375500A, Kulite with 1% accuracy, Kulite Co. Ltd., Leonia, New Jersey, USA) to measure the flow rate, in addition to a test pump and spray nozzle. The electrical signal measured by the flow meter was converted by a flow monitor (KM2 Series, Kyongin Instruments, Seoul, Korea) to LPM, and all measured signals were stored on a computer through a data acquisition system executing in-house LabView code. For the spray image acquisition and droplet size measurement, the liquid

List of pesticide injection pumps and their specifications

Pump

Model

Input voltage

Control

Max. flow rate

Max. pressure

Pump 1 Pump 2 Pump 3

Singflo Flo-2203a) BPP-25 b) Unbranded/generic c)

DC 12 V DC 22–25 V DC 12 V

Voltage control Pulse width modulation (PWM) control Voltage control

2.6 L/min 3.5 L/min 5.5 L/min

4.83 bar 10 bar 9 bar

a)YOUME ELECTRIC CO.,LTD., Xiamen, China b)JMRRC Co. LTD., Guangdong, China c)ProPumps Co., China

J. Biosyst. Eng. 1. Compressor 2. Water remover 3. Air-pressure tank 4. Pressure regulator 5. Water-pressure tank 6. Mass flow controller 7. Pressure sensor 8. Nozzle 9. Receiving optics 10.Transmitting optics 11.3D traversing system 12.Ar+ laser 13.Nd:Yag laser 14.Power supply 15.Synchronizer 16.Image processor 17.CCD camera 18.Traverse controller 19.Oscilloscope 20.PDA processor 21.Injection driver 22.Pulse generator 23.MFC controller 24.DAQ computer

Fig. 1 Drop size and drift potential measurement systems using phase Doppler analyzer (PDA) system for droplet sizing and velocity measurement

was supplied from a compression tank pressurized by compressed nitrogen gas (up to 120 bar) to the nozzle. The spray images were acquired using a single image acquisition function of a two-dimensional particle image velocimetry (PIV) system (TSI Co., Minnesota, USA), for quantitatively evaluating the spray atomization process in terms of the spray structure, spray development process, and spray angle (Dorr et al. 2013). The PIV system consisted of a laser light source (Dual Nd:YAG Laser, 120 mJ/pulse, 14.5 HZ, Big SKY Laser Co. Ltd., Motana, USA) for irradiating the spray; a charge-coupled device camera (POWERVIEW Plus 2MP, 1600 × 1200, 30f/s, TSI Co., Minnesota, USA) for collecting scattered light from the spray; a synchronizer (Laser Pulse Synchronizer 610034, TSI Co., Minnesota, USA) for synchronizing the camera and laser light source; and, an Insight 3G SOFTWARE (TSI Co., Minnesota, USA) for interpreting the collected image data.

Spray Droplet Sizing The average droplet size was measured using a phase Doppler analyzer system (PDA, Dantec Dynamics Co. Ltd., Skovlunde, Denmark) to investigate the microscopic properties of the spray (Nuyttens et al. 2007). The PDA system consisted of a manipulator including a prism for spectralizing light emitted from a continuous Ar-ion laser (air-cooled, 750 mW), used as a light source for liquid spray irradiation to green (532 nm) and blue (488 nm), and a Bragg cell (40 MHz) for frequency shift, as required for negative velocity measurement; a transmitting optic for integrating the spectroscopic and frequency-modulated lights into a measured volume; a receiving optic for collecting light scattered by the

droplets; a photomultiplier tube for converting the collected light into an electrical signal; a shutter width adjuster for evaluating the phases difference from the signals; and, a signal processor for calculating the droplet size using the input signal based on its dedicated SOFTWARE, SizeWare. The droplet size was measured 200 mm from the nozzle tip, according to ANSI/ASAE S572.1 guidelines (2009) (200–500 mm), and the average droplet diameters such as Dv0.1, Dv0.5, and Dv0.9 were measured ((ANSI/ASAE S572.1(2009); ASTM E799-03(2003).

Results and Discussion Performance Evaluation of Injection Pumps Most of the pumps used in agricultural drones in South Korea are made in China; the maximum flow rate is in the range of 2 to 5 LPM (0.53–1.32 GPM), and the maximum pressure is in the range of 4 to 9 bar (58 to 130 psi). These flow and pressure ranges satisfy the performance required by the nozzles: 15 to 60 psi (1 to 4.2 bar) for the XR series, and 15 to 100 psi (1 to 6.9 bar) for the AI series. Most pumps made in China are not provided with a performance curve, so it is difficult to understand the performance of the pump, making it difficult to set the optimum injection pressure required by the nozzle for adjusting the droplet size. Fig. 2 shows the results for the pumps 1, 2, and 3 used in the experiment; it also shows P-Q curves for each, for confirming the basic performance of the pump and the injection flow rate with a nozzle installed. In the performance evaluation results of pump 1 (widely used in domestic agricultural drones), the maximum flow rate

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XR11001-VS TX VS-06 TP11001-VK

1.5 1.0

TP11002-VS AI11002(50)

Pump P-Q curve

TX VS-06 TP11001-VK

1.5

TX VS-04 TP1100067-SS

1.0

PumpP-Q curve

TX VS-04 TP1100067-SS

1.0 0.5

0.0

0.0

0.0

1

2

1.5

1.6

3

1.7

P (bar)

4

1.8

1.9

Pump Current (A)

5 2.0

6 2.1

2.2

0

1 0.88

2 0.9

3

4

5

0.94

0.96

0.98

P (bar) 0.92

Pump current (A)

6 1

XR11001-VS TX VS-06 TP11001-VK

1.5

0.5

1.4

0 1.02

XR110015-VS AI110015(100)

2.0

0.5

0

TP11002-VS AI11002(50)

2.5

XR110015-VS AI110015(100)

2.0

Q(LPM)

2.0

Q(LPM)

2.5

XR110015-VS AI110015(100)

Q(LPM)

TP11002-VS AI11002(50)

Pump P-Q curve

2.5

1

2

3

P (bar)

4

5

6

0.6 0.8 1.0 1.2 1.4 1.6 1.8 2.0 2.2 2.4 2.6

Pump current (A)

Fig. 2 P-Q performance curves of pump-motor assembly applied in agricultural drones

is 2.37 LPM, i.e., 9% lower than the value given in the technical specifications; the maximum pressure is similar to the value given in the specifications. Looking at the P-Q curve for pump 1 when a nozzle is installed, each nozzle shows a value close to the required flow rate at a reference pressure of 2.76 bar (40 psi). As shown in the P-Q curve, the limit for this pump is 4 bar (60 psi) for a 0.57 LPM (0.15 GPM) nozzle and 3.5 bar (50 psi) for a 0.76 LPM (0.2 GPM) nozzle, and this pump seems suitable for the low flow rate (Nozzle Tip Color code: Orange and Green) spraying of XR and TP series nozzles. In regards to the performance evaluation results of pump 2, it satisfies the capacity range of most of the nozzles used in South Korea, and the P-Q performance curve is ideally distributed, showing the best performance among the three pumps used in the test. In the performance evaluation results of pump 3, not only is there a significant shortage in the maximum flow rate and pressure as compared to the values presented in the specifications but also the P-Q performance curve is abnormal. In particular, the limit for this pump is 2.76 bar (40 psi) for a 0.57 LPM (0.15 GPM) nozzle, and 2.0 bar (30 psi) for a 0.76 LPM (0.2 GPM) nozzle; thus, it would be difficult to use this pump in agricultural drones. These results indicate that if the performance of a pump in the pesticide injection system of a drone does not meet the specification requirements, the pesticide injection flow rate and expected droplet size cannot be achieved. Therefore, the performance curve of a pesticide injection pump mounted on an agricultural drone must be inspected in advance.

Flow Rate Measurement of Nozzles To evaluate the performances of the nozzles used in agricultural drones, 18 nozzles were tested, for verifying the difference between the injection flow rate provided by the manufacturer and the actual injection flow rate. The results are shown in Fig. 3. For agricultural nozzles, as suggested in ANSI/ASAE S572.1 (2009), the injection flow rate at an injection pressure of 2.76 bar (40 psi) is provided in the form of a nozzle tip color

code. Among the nozzles tested, the TX VS-04, TP800067, and TP1100067 nozzles showed a slightly smaller injection flow rate than the expected injection flow rate of 0.25 LPM (0.067 GPM). The remaining nozzles showed values similar to the expected injection flow rate (within ± 3.5%) regardless of the nozzle shape, and the injection flow rate increased in proportion to the 0.5th power ($Q = \Delta p0.5$) of the injection pressure. Therefore, if the capacity of a pesticide injection pump is within a range that satisfies the nozzle operating range, the flow rate range indicated by the nozzle color code is reliable to use for selecting a nozzle.

Evaluation of Spray Structure and Spray Angle Fig. 4 shows the results for an injection pressure of 2.76 bar among the images obtained using the PIV system at injection pressures of 1.03, 2.07, 2.76, 4.14, and 5.17 bar (15, 30, 40, 60, and 75 psi), for evaluating the spray atomization characteristics of the nozzles used in the experiment. The processes of spray development are illustrated. The spray structures of the XF, TP, and AI nozzles (flat fan nozzles) and TX nozzles (hollow cone nozzles) are all symmetrical, with a relatively high droplet number density observed in the center of the spray near the nozzle tip. For the AI nozzle, a low number density of relatively large droplets is observed, unlike in the other three nozzles. The spray angle was measured based on the spray image according to the change in injection pressure, and the results are shown in Fig. 5. The spray angle of agricultural nozzles is a very important variable in nozzle design, as it determines the spraying area and, for boom sprayers, has a great influence on the distribution of the injection flow rate according to the nozzle spacing. As the spray angle increases, the droplet diameter becomes smaller while the spatial distribution becomes wider; thus, the spray angle is particularly important for agricultural drones equipped with one to four nozzles. Looking at the spray angles of the XR series nozzles, the XR80 (80° spray angle as suggested by the manufacturer) has a spray angle of 95 to 100° at 2.76 bar (40 psi), and the XR110 (110° spray angle as suggested by the manufacturer) has a spray angle of

J. Biosyst. Eng. Fig. 3 Injection flow rate (liters per minute (LPM)) with injection pressure (bar) and nominal flow rate at 2.76 bar (40 psi)

120° or larger; these results are approximately 10% larger than the spray angles suggested by the nozzle manufacturer. For the TX series nozzles, the spray angle presented by the manufacturer is 80° at 7 bar (100 psi). However, the TXVS-04 and TX VS-08 have spray angles exceeding 80°, and the TXVS06 and TX VS-12 have spray angles near 80°, but lower. This indicates a very large spray change among the TX series nozzles with a hollow cone spray structure. The spray angles of the TP series nozzles match best with the spray angles (80° and 110° at 2.76 bar (40 psi)) presented by the manufacturer, even with some deviations. The spray angles of the AI series nozzles are different depending on the injection flow rate; the spray angle of the AI11002-VS nozzle matches very well with the spray angle of 110° presented by the manufacturer. As there is a difference (maximum of 10%) between the spray angle suggested by the nozzle manufacturer and actual spray angle, depending on the nozzle, the results of the spray angle measurement must be referred to when setting the nozzle spacing and overlap of spray patterns. In addition, as the -20 -15 -10 -5

0

5

spray angle increases almost linearly as the injection pressure increases, the pre-set injection pressure must be observed when spraying using a drone.

Droplet Sizing of Sprays The atomization characteristics (average droplet size, size distribution, uniformity) and flow characteristics (velocity distribution) of the nozzle are factors directly affecting the adhesion rate and drift characteristics of the spray droplets. Therefore, a droplet size evaluation must precede sprays under very complicated flow field (downwind and sidewind) conditions, such as sprays using agricultural control drones. In addition, the nozzles should form a droplet size distribution that can reduce or minimize spray drift. Many studies related to spray drift potential have suggested that the drift potential can be reduced when the average droplet size (volume median diameter (VMD) or Dv0.5) is at least 200 μm (Czaczyk et al. 2012; Fritz et al. 2012).

10 15 20

5

10 15

20 25

30 35 40

a) XR8001-V

(b) TX VS-06

(c) TP8001-VS

(d) AI110015

Fig. 4 Spray images at injection pressure of 2.76 bar (40 psi) (a XR8001-VS (Q = 0.38 LPM), b TX VS-06 (Q = 0.38 LPM), c TP8001-VS (Q = 0.38 LPM), d AI110015 (Q = 0.57 LPM))

J. Biosyst. Eng. Fig. 5 Spray angles with injection pressures and nominal spray angle at an injection pressure of 2.76 bar for XR, TX, TP, and AI series. a XR series. b TX series. c TP series. d AI series

(a) XR series

(b) TX series

(c) TP series

(d) AI series

Fig. 6 shows the VMD (Dv0.5) and relative span factor (RSF) together, for evaluating the atomization characteristics of the nozzles used in the test. As mentioned above, VMD is the volume medial diameter, and RSF is a dimensionless index indicating the degree of dispersion of the droplet size distribution. It is defined by RSF = (Dv0.1–Dv0.9)/Dv0.5. The XR series nozzles have droplet size ranges suggested by the manufacturer in the ranges of fine (orange, 144 to 235 μm) and very fine (VF) (61 to 144 μm, at 4.14 bar (60 psi)), but the experimental results are in the range of 80 to 120 μm, indicating a droplet size distribution close to VF (red, 61 to 144 μm) (color code: Fritz et al. 2012). In particular, many small droplets of approximately 80 μm are present in the center of the spray with a high number density, and thus the spray is very vulnerable to spray drift characteristics. These droplets decrease as the injection pressure increases. The TX series nozzles are manufactured to have a droplet size range of VF (red, 61 to 144 μm), and the experimental results show a droplet size range of approximately 50 μm in the center of the spray and 120 μm in the outer area of the spray. The TP series nozzles have a droplet size range suggested by the manufacturer in the range of fine (orange, 144 to 235 μm), but the experimental results are in the range of 90 to 120 μm, indicating a smaller droplet size distribution, i.e., closer to VF (red,

61 to 144 μm). The RSF is in the range of 0.2 to 1.1 for the XR series nozzles, 0.3 to 1.0 for the TP series nozzles, and 0.2 to 1.2 for the TX series nozzles, indicating that the uniformity of the XR and TP series nozzles is better than that of the TX nozzle. The outer area of the spray shows a low RSF while the central area of the spray shows a high RSF, indicating that the central area is composed of large and small droplets. Fig. 7 shows the weighted mean VMD (WMDv0.5) of DV0.5 (see Fig. 6) as measured along the radial direction at 200 mm below the nozzle tip, considering the droplet density at each measurement point. The WMD v0.5 tends to decrease with increasing injection pressure, regardless of the spray angle. Among the nozzles with a spray angle of 80°, TP8001 shows the largest droplet size, followed by XR and TX. The nozzles with a spray angle of 110° show a droplet size slightly smaller than that of the nozzles with a spray angle of 80°. This is because the initial droplet size is reduced, owing to the decrease in the thickness of the liquid film as the spray angle increases. These results are obtained by converting the droplet size range suggested by the manufacturer into the mean value after considering the weight for the number density, which may be used as a more quantitative value when selecting a nozzle.

J. Biosyst. Eng. 150 140 130 120 110 100 90 80 70 60 50 40 -250-200-150-100 -50 0

150 140 130 110 100 90 80 70

P=2.07bar P=2.76bar P=4.14bar

60 50 40 -250 -200 -150 -100 -50

0

50 100 150 200 250

1.4

1.0 0.8 0.6 0.4 0.2 0.0 -250-200-150-100 -50 0

50 100 150 200 250

Relative Span Factor

Relative Span Factor

1.4 P=2.07bar P=2.76bar P=4.14bar

50 100 150 200 250

Radial Distance (mm)

Radial Distance (mm)

1.2

P=2.07 bar P=2.76 bar P=4.14 bar

Radial Distance (mm)

P=2.07 bar P=2.76 bar P=4.14 bar

1.2 1.0 0.8 0.6 0.4 0.2 0.0 -250-200-150-100 -50 0

Radial Distance (mm)

1.4

Relative Span Factor

Dv0.5(μm)

120

150 P=2.07 bar 140 P=2.76 bar 130 P=4.14 bar 120 110 100 90 80 70 60 50 40 -250-200-150-100 -50 0 50 100 150 200 250

P=2.07 bar P=2.76 bar P=4.14 bar

1.2 1.0 0.8 0.6 0.4 0.2 0.0 -250-200-150-100 -50 0

50 100 150 200 250

(a) XR8001-VS

50 100 150 200 250

Radial Distance (mm)

Radial Distance (mm)

(b) TP8001-VS

(c) TX VS-06

Fig. 6 Volume medial diameter (VMD, Dv0.5) and relative span factor distribution at an axial distance of 200 mm from the nozzle tip. a XR8001-VS. b TP8001-VS. c TX VS-06

Conclusions This study was conducted to verify whether the characteristics of typical spray pumps and nozzles for the pesticide spray systems of agricultural drones currently used in South Korea are consistent with those suggested in the product specifications, and to induce the selection of proper pumps and nozzles by providing experimentally proven quantitative data. To this end, the performances of three types of pumps and 18 types of nozzles currently in use were evaluated in terms of the pressure-flow rate (P-Q) curve, injection flow rate, spray angle, and droplet size. The results are summarized as follows. For a pesticide injection pump, the maximum pressure and P-Q curve must include the ranges of the injection pressure

120

120 TP8001-vs TX VS-06 XR8001-VS

110

WMDV50

110

WMDV50

Fig. 7 Mean VMD (Dv0.5) at an axial distance of 200 mm from the nozzle tip. a Spray angle of 80°. b Spray angle of 110°

and the injection flow rate of the nozzle. As the pesticide spray characteristics are a function of the injection pressure, verification is required prior to mounting an injection pump to a drone to ensure the performance of the nozzle. While most of the 18 types of nozzles used in the test showed results matching the flow rates suggested by their manufacturers, the spray angles of the XR series and TX series nozzles showed differences of up to 10% and 7%, respectively; the flow rates of the TP and AI series nozzles were measured to be close to the values suggested by the manufacturer. Therefore, when installing nozzles using a boom on a drone, it is necessary to determine the spraying range while considering the spray angle error. The droplet size of the XR, TX, and TP series nozzles (as measured at 200 mm below the tip of the

100 90

100 90

80

80

70

70

2.07

2.76

3.45

4.14

XR11001VS TP11001-VK

2.07

2.76

3.45

4.14

Pressure (bar)

Pressure (bar)

(a) spray angle of 80 deg.

(b) spray angle of 110 deg.

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nozzle) was slightly smaller than the droplet size suggested by the manufacturer. The RSF was in the range of 0.2 to 1.1 for the XR nozzles, 0.3 to 1.0 for the TP nozzles, and 0.2 to 1.2 for the TX nozzles. In addition, it was confirmed that the WMDv0.5 can be used as a useful quantitative index for selecting a nozzle. Funding This work was carried out with the support of “Research Program for Agriculture Science and Technology Development (Project No. PJ013819),” National Institute of Agricultural Science, Rural Development Administration, Republic of Korea.

Compliance with Ethical Standards Conflict of Interest The authors declare that they have no conflict of interest.

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Original Article

Drone-Based Pesticide Application: Efficacy, Optimisation, and Standardisation for Sustainable Crop Protection Rittik Sarkar1*, Rajna S2, Avirup Roy3, Abithaa P4, Yuvaraj H M5 and Anu Gimmy2 1Department of Entomology and Agricultural Zoology, Institute of Agricultural Sciences, Banaras

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ABSTRACT The rapid advancement of unmanned aerial vehicles (UAVs), popularly known as spray drones, is transforming agrochemical application practices across diverse cropping systems. This review synthesises recent evidence from rice, wheat, cotton, legumes, pulses, jute, and perennial orchards to evaluate their efficacy, optimisation parameters, and potential for standardisation. Findings consistently show that UAV spraying can achieve pest and disease suppression comparable to, and in many cases exceeding, conventional knapsack and air-blast sprayers, while using substantially lower spray volumes. Critical determinants of success include flight altitude, forward speed, nozzle type, droplet spectrum, and the use of adjuvants or tank-mixes. Properly optimised UAV operations enhance canopy penetration, reduce drift, improve pesticide-use efficiency, and increase farmer profitability. Beyond pest management, UAVs have proven effective in delivering foliar nutrients and defoliants, highlighting their versatility. However, methodological inconsistencies in spray evaluation, coupled with regulatory gaps and the absence of UAV-specific pesticide labels, remain barriers to wider adoption. The integration of harmonised evaluation protocols, ISO-aligned efficiency metrics, and best management practices will be essential for regulatory acceptance. With further refinement of stage-specific optimisation, formulation science, and digital agronomy tools, UAV spraying offers

a scalable, sustainable pathway for crop protection that aligns with global demands for precision agriculture and environmental stewardship. Keywords: Unmanned aerial vehicles (UAVs); Droplet deposition and drift; Flight parameters; Pesticides use efficiency; Precision agriculture 1. INTRODUCTION 1.1. Why drones for crop protection now Labour scarcity, timeliness constraints at pest outbreaks, and the need to reduce water and pesticide footprints are pushing applicators toward compact, rapidly deployable platforms. Multi-rotor UAVs have emerged as particularly suitable for diverse and heterogeneous cropping landscapes, including flooded rice fields, terraced systems, and perennial orchards. Their ability to navigate complex terrains, deliver high field efficiency in smallholder-dominated mosaic farming, and minimize crop damage compared to conventional tractor-mounted booms has been well documented, from the pioneering adoption in East Asia to more recent applications in Indian farmlands and U.S. orchards (Li et al., 2020; Subramanian et al., 2021). In field studies spanning cotton, rice and moong, optimised UAV settings achieved meaningful pest suppression within days, with reduced labour and operational water compared with conventional methods (Parmar et al., 2021). 1.2. Evidence that efficacy can match conventional methods A recurring concern is whether very low carrier volumes can deliver enough active ingredient (a.i.) to the biologically relevant strata. In almonds, UAV applications at 46.8-93.5 L ha-^{1} achieved comparable whole-nut chlorantraniliprole residues to an air-blast sprayer operating at ~935 L ha-^{1}, with measurable penetration into lower canopy layers and acceptable navel orangeworm outcomes (Li et al., 2020). In rice, small-plot and farm-scale studies show that flight height and speed tune droplet distribution and planthopper control: a 1.5 m height at ~5 m s -^{1} maximised lower-canopy deposition (CV ≈ 23%) and yielded 92-74% efficacy over 3-10 days after treatment (Qin et al., 2016). Trials from Punjab Agricultural University further demonstrated significant main effects of height and forward speed on whitefly and brown planthopper suppression across crops, with lower heights (0.5-0.75 m) and slower passes

(2-3 m s-¹) frequently outperforming faster, higher settings (Parmar et al., 2021). 1.3. The optimisation problem: physics, formulation, and flight UAV spraying is a coupled system: rotor downwash structures canopy airflows, nozzles and adjuvants shape droplet spectra and spreading, and meteorology gates drift and evaporation. Recent rice work quantified how tank-mix adjuvants that lower surface tension and adjust viscosity can shift droplet size distributions toward more deposition-efficient ranges, reducing drift and improving planthopper control by 20-35% versus no-adjuvant controls peaking near ~0.5% v/v (Wang et al., 2024). In parallel, growth-stage-specific parameter maps are emerging: in japonica rice, pesticide-use efficiency varied with speed (3-5 m s-¹) and nozzle type (e.g., F110-015 vs F110-025), with recommendations differing across tillering, jointing, and booting stages (Zhou et al., 2020). Economically,

drone-assisted

tank-mix

programs

that

pair

diamide

insecticides

with

triazole/strobilurin fungicides in paddy have delivered higher benefit–cost ratios than single-actives

under Indian field conditions, even after accounting for service fees (illustrative treatments combining tetraniliprole or chlorantraniliprole with tebuconazole+trifloxystrobin) (Ragiman et al., 2024).

1.4. Measuring what matters: deposition, drift, and efficiency Comparisons of WSP versus glass collectors under UAV passes show method-dependent absolute deposition, underscoring that trend-wise comparisons are more robust than raw magnitudes across materials (Ahmad et al., 2022). Moreover, digital stain-analysis tools (DepositScan; SprayDAT) can substantially under-estimate total volume at higher stain coverage because overlapping stains depress apparent droplet counts; cross-checking with colorant extraction and speed-based flow predictions is advised (Koo et al., 2024). For integrated performance reporting, ISO-aligned pesticide-use efficiency metrics that combine measured deposition with leaf area index (LAI) offer a path to comparable results across growth stages, provided the LAI method is standardised and nonleaf sinks (e.g., stems, panicles) are appropriately handled (Zhou et al., 2020). Figure 1. Influence of UAV flight height and downwash airflow on spray deposition and drift distribution in crop canopies (Lan et al., 2021). 2. Cross-Crop Efficacy of UAV-Based Agrochemical Application 2.1. UAV spraying in Rice Rice has been the proving ground for UAV pesticide application, particularly in East and South Asia. Early Chinese studies established that UAVs could provide effective control of brown planthopper (Nilaparvata lugens) when flown at 1.5 m altitude and 5 m s-¹, achieving 92-74% suppression over 10 days outperforming stretcher-mounted sprayers in both deposition uniformity and biological efficacy (Qin et al., 2016). Follow-up evaluations confirmed that UAVs could also suppress rice stem

borer (Chilo suppressalis), with efficacy exceeding 90% when single-rotor UAVs were flown at 2-4 m altitude and 3-4 m s-¹ (Wang et al., 2016). At the institutional level, Tamil Nadu Agricultural University validated UAV spraying under Indian smallholder conditions, reporting successful brown planthopper control with significant reductions in water use compared to knapsack methods (Subramanian et al., 2021). Rice disease control has also been demonstrated. UAV-applied fungicides suppressed sheath blight (Rhizoctonia solani) by 75-77% and reduced grain discoloration by up to 78% when tetraniliprole was tank-mixed with triazole–strobilurin

fungicides (Ragiman et al., 2024). Comparable levels of protection were achieved against rice blast and rice leaf roller at 18 L ha-¹ when methylated crop oil adjuvants were included, highlighting the role of formulation optimisation (Wang et al., 2020). 2.2. Cotton and legumes: adapting UAVs to broadleaf crops Cotton represents a contrasting challenge due to larger canopies and common reliance on whitefly management. Optimised UAV passes at 0.5-1.0 m altitude and 2 m s-¹ reduced whitefly populations by 84.8% at 7 days after spraying (Parmar et al., 2021). In Xinjiang, UAVs were further employed for cotton defoliant application ahead of mechanised harvesting. At 48 L ha-¹ and 1.5 m altitude, boll opening was effective, showing that drones can extend beyond pest management to harvest facilitation (Liao et al., 2019). Pulses are emerging beneficiaries. In moong bean, UAVs applied insecticides effectively against sucking pests, while in black gram, foliar nutrient sprays delivered by drones increased grain yields to 784 kg ha-¹ exceeding knapsack application (Nandhini et al., 2022). Nutrient UAV spraying in maize likewise boosted leaf area index and yields beyond 7 t ha-¹, demonstrating versatility of drones for both protection and plant nutrition (Kaniska et al., 2022). 2.3. Wheat, maize, and jute: extending to cereals and fibre crops Wheat trials confirm UAV efficacy against both insects and diseases. Sprays at >16 L ha-¹ with coarse nozzles-controlled aphids and powdery mildew comparably to electric knapsack sprayers (Wang et al., 2019). Disease control in wheat with triadimefon applied via UAV achieved ~55% reduction of powdery mildew at standard label rates, indicating scope for dose optimisation (Qin et al., 2018). Herbicide delivery via UAV also proved effective: drone applied post emergence metribuzin reduced weed pressure in wheat, especially when combined with pre-emergence knapsack spraying (Pranaswi et al., 2024). Beyond cereals, Bangladesh field experiments showed UAV insecticide applications in jute effectively suppressed hairy caterpillar and semilooper populations, reducing labour requirements by 60% compared to manual methods (Alam et al., 2024).

2.4. Orchards and high-value crops Large-canopy systems such as almonds present one of the toughest UAV challenges. Yet, UAV applications at 46-93 L ha-¹ achieved comparable chlorantraniliprole residues to conventional airblast spraying at 935 L ha-¹, penetrating lower canopy strata and effectively reducing navel orangeworm infestation (Li et al., 2020). This efficiency gain underscores UAVs' potential for perennial orchards, provided flight patterns are tuned to canopy architecture.

Figure 2. UAV-based pesticide application in orchard and perennial crop systems.

2.5. Global scope of efficacy evidence Across crops, UAVs consistently achieve pest and disease suppression comparable to or better than conventional spraying, often with lower spray volumes, higher efficiency, and reduced operator exposure. Trials in China, India, the U.S., Pakistan, and Bangladesh collectively validate UAVs as broadly applicable tools though crop-specific calibration remains critical (Nordin et al., 2021).

Table 1. Cross-crop efficacy of UAV-based agrochemical application compared with conventional spraying systems Crop

Target

UAV parameters

Main findings

Reference

Brown

1.5 m height; 5 m

92-74%

planthopper

s^{-1}

efficacy

Rice

Stem borer

2-4 m height

> 90% suppression

Wang et al. (2016)

Cotton

Whitefly

0.5-1.0 m; 2 m s^{-1}

84.8% reduction

Parmar

pest/disease Rice

control

Qin et al. (2016)

et

al.

(2021) Wheat

Aphid & powdery mildew

> 16 L ha^{-1}

Comparable

to

Wang et al. (2019)

knapsack spraying

Almond

Sarkar et al

46-93 L ha^{-1}

Navel

Comparable

orangeworm Jute

Hairy caterpillar

residue

Li et al. (2021)

to air-blast sprayer UAV

insecticide

60% labour saving

Alam et al. (2024)

Higher

Nandhini

spraying Black

Foliar

gram

spray

nutrient

UAV

foliar

application

yield

than

conventional spray

et

al.

(2022)

- Deposition Dynamics and Drift Behaviour 3.1. Fundamentals of UAV-driven deposition Unlike tractor booms or aerial fixed-wing aircraft, UAVs rely on rotor-induced downwash to transport droplets into the canopy. This airflow redistributes spray laterally and vertically, producing distinct deposition profiles that depend on flight height, speed, rotor type, and nozzle configuration (Wang et al., 2016; Zhou et al., 2020). Studies in rice and cotton reveal that low-altitude flights (1.5-2.0 m) with moderate forward speed (3-4 m s^{-1}) enhance canopy penetration while maintaining acceptable uniformity of deposition (Qin et al., 2016; Parmar et al., 2021). 3.2. Vertical distribution within the canopy Deposition stratification is a consistent observation in UAV trials. For instance, rice trials using watersensitive paper (WSP) cards documented higher coverage in the upper canopy and reduced deposition in the basal layers, particularly at later crop growth stages (Weicai et al., 2023). Use of adjuvants mitigates this decline by increasing droplet adhesion and reducing bounce-off, allowing droplets to remain on erectophile leaves. In cotton, centrifugal nozzles at lower flight heights provided improved coverage of the upper and mid canopy compared with hydraulic nozzles, though sugarcane benefited more from the latter due to denser architecture (Ranabhat and Price, 2025). 3.3. Nozzle, droplet size, and formulation effects Droplet spectrum is a key determinant of drift versus retention. Flat-fan nozzles produced finer droplets and better canopy penetration in rice compared with air-induction nozzles, though with increased drift risk (Wongsuk et al., 2024). Tank-mix adjuvants significantly improved spray deposition by lowering surface tension and increasing viscosity; in rice, 0.5% v/v adjuvant addition improved brown planthopper control efficacy by 20-35% over non-adjuvant sprays (Wang et al., 2024). Formulation optimisation has therefore become central to maximising UAV efficiency while minimising drift losses. 3.4. Rotor type and UAV design Aircraft design influences droplet movement. Single-rotor UAVs created more uniform deposition patterns compared to multi-rotor systems, especially at 2-4 m altitudes, achieving over 90% control of stem borer in rice (Wang et al., 2016). Conversely, eight-rotor UAVs generated stronger downward airflows than quadcopters, leading to greater overall deposition, particularly when coupled with flat-

fan nozzles and adjuvants (Wongsuk et al., 2024). This highlights that UAV configuration should be tailored to crop type and canopy density. 3.5. Drift and off-target movement Drift remains a major challenge for UAV spraying. Small droplets (<100 μm) are highly susceptible to off-target transport, particularly under windy conditions (Knoche, 1994; Subramanian et al., 2021). Trials show that drift losses increase with flight height, but can be mitigated by using adjuvants, coarser nozzles, and optimised swath overlap (Wang et al., 2020). 3.6. Comparative deposition efficiency Relative to ground knapsack sprayers, UAVs often achieve similar or superior canopy penetration with much lower water volumes. For example, almond orchards treated with UAVs at 46-93 L ha^{-1} showed comparable chlorantraniliprole residues to air-blast sprayers operating at nearly

935 L ha-¹ (Li et al., 2020). In rice, pesticide-use efficiency ranged from 47-56% with UAVs, compared to 3842% for knapsack sprayers, underscoring better deposition per unit of active ingredient (Zhou et al., 2020). 4. Optimisation Strategies for UAV Spraying 4.1. Flight height and forward speed Optimal combinations of flight height and speed are critical to balance deposition uniformity and drift. In rice, 1.5 m flight height at ~5 m s-¹ maximised droplet coverage across canopy strata, achieving superior planthopper control compared with stretcher-mounted sprayers (Qin et al., 2016). Similarly, wheat and cotton trials revealed that lower altitudes (0.5-1.5 m) combined with moderate speeds (2-3 m s-¹) improved spray penetration and reduced off-target losses (Parmar et al., 2021; Wang et al., 2016). Conversely, excessive heights (>3 m) increased drift and reduced lower canopy deposition, underscoring the need for fine-tuned passes aligned to crop stature and density (Weicai et al., 2023). 4.2. Nozzle selection Nozzle choice dictates droplet spectrum and deposition efficiency. Flat-fan nozzles generate finer droplets with better canopy penetration but greater drift risk, while air-induction nozzles produce coarser droplets that reduce drift but limit penetration (Wongsuk et al., 2024). For cereals like rice and wheat, flat-fan nozzles at low altitudes were preferable; for taller or denser canopies (sugarcane, cotton), centrifugal or hydraulic nozzles at adjusted heights improved deposition uniformity (Ranabhat and Price, 2025). 4.3. Spray volume optimisation Unlike ground sprayers applying hundreds of litres per hectare, UAVs typically operate at ultra-low volumes (10-50 L ha-¹). Trials in wheat showed that increasing spray volume from 9 to >16 L ha^{-1} improved control of aphids and powdery mildew, with coarse sprays enhancing leaf surface retention (Wang et al., 2019). In almonds, UAV sprays at 46-93 L ha^{-1} delivered equivalent residues to 935 L ha-¹ via air-blast sprayers, suggesting that efficiency gains are possible without compromising

efficacy (Li et al., 2020). Rice trials further demonstrated pesticide-use efficiencies of 47-56% with UAVs, significantly higher than 38-42% for knapsack sprayers (Zhou et al., 2020). 4.4. Role of adjuvants and tank-mixes Formulation enhancement plays a decisive role in UAV spraying. Tank-mix adjuvants improved droplet spreading, adhesion, and reduced drift. For instance, in rice, 0.5% methylated vegetable oil adjuvant increased deposition uniformity and improved brown planthopper control by 20-35% compared with water-only sprays (Wang et al., 2024). Similarly, UAV-applied pesticide tank-mixes (e.g., tetraniliprole + triazole–strobilurin fungicides) provided integrated insect and disease suppression, yielding up to 7995 kg ha^{-1} of rice and benefit-cost ratios exceeding 1:5.6 (Ragiman et al., 2024). 4.5. Crop growth stage considerations Deposition patterns shift with crop phenology. In rice, denser canopies at booting and heading reduced basal deposition; UAV efficacy was maximised when parameters were tailored to crop stage (Weicai et al., 2023). In cotton, defoliant UAV sprays ahead of harvest were optimised at 48 L ha^{-1}, 1.5 m altitude, and ~3 m s-¹ speed (Liao et al., 2019). For legumes like black gram, drone-based foliar nutrient sprays at reproductive stages increased pod number and yield significantly over manual application (Nandhini et al., 2022). 4.6. UAV design and rotor configuration Aircraft design dictates deposition uniformity. Single-rotor UAVs generated more consistent coverage than multi-rotor drones in rice, though the latter were easier to operate in fragmented fields (Wang et al., 2016). Eight-rotor drones produced stronger downwash than quadcopters, improving penetration and efficacy, especially when paired with adjuvants (Wongsuk et al., 2024). This suggests rotor configuration should be selected based on crop size, canopy complexity, and field conditions. Table 2. Recommended operational parameters for UAV spraying in major crops Crop

Flight

Speed

Spray

height

(m s^{-1})

volume

1.5-2.0

(L

Reference
nozzle
ha⁻¹)
(m) Rice
Preferred
3-5
18-30
Flat-fan
Qin
et
al.
(2016);
Wang et al. (2020) Cotton
0.5-1.5
2-3
30-48
Centrifugal
Parmar et al. (2021)
Wheat
1.5-2.0
3-4

> 16

Coarse
Wang et al. (2019)
spray
nozzle Almond
2-3
3-4
46-93
Hydraulic
Li et al. (2021)
nozzle Sugarcane
2-3
2-4
30-50
Hydraulic
Ranabhat
nozzle
(2025)
&

Price

- Standardisation of UAV Spray Evaluation Methods 5.1. Challenges in evaluating UAV deposition Assessing UAV spray performance is inherently complex because deposition patterns are less uniform than those produced by tractor-mounted booms. Traditional evaluation relies heavily on watersensitive papers (WSPs), which register droplet density, size, and coverage. However, WSPs can overestimate deposition due to stain enlargement and fail to capture droplets <50 µm, leading to systematic errors (Ahmad et al., 2022). Glass strips and polyester collectors have been tested as alternatives, providing more accurate quantification of fine droplet residues but missing broader spatial variability. This highlights the absence of a universally accepted sampling standard. 5.2. Digital analysis tools: DepositScan vs. SprayDAT For over a decade, DepositScan has been widely used to analyse scanned WSPs, estimating droplet size distribution and volume from stain geometry. Yet UAV-specific studies show that DepositScan underestimates spray volume by up to 2.7-fold compared with spectrophotometric extraction of tracer dyes (Koo et al., 2024). More critically, overlapping stains at high coverage led to merged droplet counts, inflating mean diameters and obscuring true droplet density. To address these limitations, SprayDAT, a Python-based batch processing tool, was recently introduced. It improves recognition of small droplets (<100 µm), processes large datasets efficiently, and allows researchers to modify spread factors for different substrates (Koo et al., 2024). Adoption of such flexible, transparent tools will be central to harmonising UAV spray research across institutions. 5.3. Cross-validation with extraction-based methods Deposition assessment should not rely solely on WSP imaging. Studies that paired WSP with tracerdye extraction from Mylar or Kraft paper sheets provided more reliable absolute deposition values. For example, spectrophotometric extraction of blue dye from Kraft paper correlated strongly with SprayDAT outputs, providing a scalable means of validating digital image analysis (Koo et al., 2024).

Such hybrid protocols reduce reliance on assumptions about spread factors and allow calibration of image-based estimates.

Figure 3. Proposed standardised workflow for evaluation of UAV spray deposition, drift, and pesticide-use efficiency (Jing et al., 2023). 5.4. Towards ISO-aligned efficiency metrics Beyond deposition, performance reporting increasingly includes pesticide use efficiency (PUE), the ratio of biologically effective deposition to total a.i. applied. In rice, UAV spraying achieved PUE values of 47-56%, outperforming knapsack sprayers at 38-42% (Zhou et al., 2020). Incorporating canopy structure, e.g. leaf area index (LAI), into these calculations ensures stage-specific comparisons. The ISO 24253 framework for field efficacy and drift assessments could provide a foundation for standardised UAV evaluation protocols if adapted for low-volume aerial systems. 5.5. Need for harmonised global protocols Current evidence highlights methodological inconsistency across studies: different collectors (WSP, glass, filter papers), image tools (DepositScan, ImageJ, SprayDAT), and tracer chemicals complicate cross-trial comparisons. Without harmonisation, results remain crop and site specific, slowing regulatory acceptance and label development for UAV applications. A minimal reporting standard (MRS) is therefore recommended: 1. Use at least two collector types (WSP for pattern, extraction-based for volume). 2. Report canopy-stratified deposition (upper, middle, lower). 3. Quantify drift at ≥2 downwind distances. 4. Specify UAV operational parameters (altitude, speed, nozzle, spray volume, adjuvant). 5. Express efficiency in ISO-aligned PUE terms.

Table 3. Comparative assessment of UAV spray deposition evaluation methods

Method
Principle
Advantages
Limitations
Reference
Water-
Droplet stain analysis
Easy
Cannot detect very
Ahmad et al.
inexpensive
fine droplets
(2022)
Accurate
Limited
measurement
quantification
coverage
(2022)
Image-based droplet
Rapid processing
Underestimates
Koo
sensitive paper
and
(WSP) Glass slides
DepositScan
Residue
deposition
analysis
volume
spatial
at
high
Ahmad et al.
et
al.
(2024)
coverage SprayDAT
Python-based
batch

analysis

Improved

small

Requires calibration

droplet

Koo

et

al.

(2024)

recognition Dye extraction

Spectrophotometric

Accurate

methods

quantification

absolute

Labour-intensive

Koo

et

al.

(2024)

deposition

- Economic, Environmental, and Safety Implications of UAV Spraying 6.1. Cost-benefit outcomes In India, UAV-delivered tank-mixes (tetraniliprole + fungicides) not only enhanced pest and disease suppression but also achieved an incremental cost-benefit ratio (ICBR) of 1:5.63, making them economically superior to conventional methods (Ragiman et al., 2024). For maize and pulses, dronebased nutrient sprays improved yield parameters beyond ground application, suggesting that UAVs can contribute not only to crop protection but also to productivity gains (Nandhini et al., 2022; Kaniska et al., 2022). 6.2. Labour and time efficiency Labour savings are substantial. UAV spraying in jute reduced manual labour requirements by nearly 60% compared to traditional backpack application (Alam et al., 2024). Similarly, UAVs cover more hectares per hour than knapsack sprayers, particularly in fragmented smallholder landscapes where tractor-mounted booms are impractical. Reduced dependence on labour also mitigates seasonal shortages, a key driver of UAV adoption in both Asia and North America (Li et al., 2020). 6.3. Operator exposure and health safety Conventional knapsack spraying exposes applicators to significant pesticide risks due to direct contact and inhalation. UAV spraying eliminates the need for human presence in the treated field during application, thereby reducing operator exposure and improving occupational safety (Subramanian et al., 2021; Pathak et al., 2020). This advantage is particularly important for

hazardous chemistries and in crops grown in waterlogged or steep terrains, where manual application can be both unsafe and inefficient. 6.4. Environmental footprint and drift reduction While UAVs often operate at low spray volumes, concerns remain regarding drift of fine droplets (<100 μm). The use of methylated vegetable oil adjuvants further reduced off-target drift by improving droplet stability and canopy retention (Wongsuk et al., 2024; Wang et al., 2024). Furthermore, the pesticide-use efficiency gains observed with UAVs (47-56% vs. 38-42% for knapsack sprayers) translate directly into reduced chemical loads per unit of effective pest control (Zhou et

al., 2020). 6.5. Barriers and equity considerations Despite these advantages, high initial costs, short battery life, limited payload capacity, and regulatory restrictions remain barriers to adoption. In developing regions, many farmers rely on service providers rather than owning UAVs, raising questions of accessibility and equitable deployment (Pathak et al., 2020). Policies that subsidise drone services, establish training programs for certified operators, and support cooperative ownership models could enhance uptake among smallholders. Table 4. Economic and environmental advantages of UAV spraying over conventional application systems Parameter

UAV spraying

Conventional spraying

Water use

Low

High

Labour requirement

Very low

High

Operator exposure

Minimal

High

Field capacity

High

Moderate

Pesticide-use efficiency

47-56%

38-42%

Crop trampling

Negligible

Moderate

Suitability in wet fields

Excellent

Poor

- Policy, Regulatory, and Adoption Challenges 7.1. Regulatory gaps in UAV spraying While UAV applications have expanded rapidly across Asia, Europe, and North America, regulatory frameworks often lag behind technological advances. In India, for example, pesticide labels are not yet standardised for low volume UAV spraying, leading to uncertainty in recommended doses and flight parameters (Pathak et al., 2020). Similarly, in the United States and the European Union, UAVs remain under strict aviation and pesticide application laws, requiring case by case exemptions for commercial use (Li et al., 2020). Without harmonised registration and label guidance, UAV applications cannot be fully integrated into national crop protection programs.

7.2. Best management practices (BMPs) Industry stakeholders have begun developing best management practices (BMPs) to bridge these regulatory gaps. FMC Corporation, for instance, outlined BMPs for UAV spraying of chlorantraniliprole products in Asia, emphasising the timing of applications before larval boring, correct droplet size classes, and flight consistency (Li et al., 2019). These BMPs represent some of the earliest

standardised operational guidelines for UAV pesticide delivery, offering a foundation for label adaptation and farmer training. 7.3. Adoption drivers and barriers Adoption of UAV spraying is shaped by both economic and social drivers. Labour shortages in China and Japan have accelerated uptake, while in India and Bangladesh, demonstrations of yield gains, labour savings, and reduced pesticide costs are encouraging farmer cooperatives to invest (Alam et al., 2024; Ragiman et al., 2024). However, barriers include high acquisition costs, dependence on service providers, lack of trained operators, and limited awareness of safety protocols (Pathak et al., 2020). In smallholder systems, cooperative UAV ownership or pay per service business models may be essential for scaling access. 7.4. International perspectives Japan pioneered UAV spraying with the Yamaha RMAX in the 1990s and continues to lead in UAVspecific pesticide registration (Li et al., 2020). China has scaled rapidly, integrating drones into government supported mechanisation programs, while Australia has deployed UAVs in broadacre farming for weed control. In contrast, European adoption is constrained by stricter aviation rules, though pilot trials are underway in vineyards and orchards (Cunha et al., 2021). The unevenness of these frameworks underscores the need for global harmonisation, particularly around operator licensing, aerial drift limits, and residue management. 7.5. Path forward: regulatory science and stakeholder alignment For UAV spraying to transition from experimental to mainstream, three regulatory priorities must be addressed: 1. Establish UAV-specific pesticide labels with recommended doses, spray volumes, and adjuvant use. 2. Mandate training and licensing programs to ensure safe UAV operation, including drift management. 3. Adopt harmonised evaluation methods so efficacy, drift, and residue data are comparable across countries. Collaborative platforms involving government agencies, research institutes, and industry are essential to accelerate regulatory acceptance and farmer adoption.

- Future Prospects and Research Priorities 8.1. Harmonised deposition and drift standards The most urgent need is a globally harmonised protocol for UAV spray evaluation. Current practice mixes

WSP,

glass/Mylar,

and

different

imaging

pipelines,

which

complicates

cross-study

comparisons. A consensus package should pair (i) pattern samplers (e.g., WSP) with (ii) extractionbased quantification (Kraft/Mylar + spectrophotometry), capped at ≤20% stain cover to avoid overlap artefacts, and (iii) batch-processable image analytics with transparent spread-factor calibration (e.g., SprayDAT). Benchmarking against known flow × speed outputs should be required for QA/QC (Ahmad et al., 2022; Koo et al., 2024). Priority actions: There is a pressing need to establish a Minimal Reporting Standard (MRS) for UAV spraying studies, mandating the inclusion of canopy-stratified deposition data, downwind drift measurements at ≥2 distances, detailed meteorological records, nozzle and droplet classification, adjuvant use, and pesticide-use efficiency (PUE) metrics aligned with ISO guidelines (Zhou et al., 2020). 8.2. Label translation for low-volume aerial rates Most pesticide labels were written for high-volume ground or manned-aircraft systems. We need bridging studies that translate label rates to ultra-low-volume (10-50 L ha^{-1}) UAV applications, with residue (MRL), efficacy, and phytotoxicity assurance across crops and phenophases (Li et al., 2020; Pathak et al., 2020). Priority actions: Collaborative consortia involving regulators, industry, and academia are essential to generate crop-specific dose volume deposition reference maps, and to develop UAV-tailored label guidelines encompassing swath width, flight altitude, operating speed, and adjuvant use. 8.3. Stage-aware optimisation playbooks Deposition declines in dense canopies late in the season; optimal settings shift with growth stage and

architecture. More trials should produce stage-specific parameter tables (height, speed, nozzle, volume, overlap) tied to LAI/plant height for cereals, pulses, and orchards (Weicai et al., 2023; Liao et al., 2019). Priority actions: Open-access datasets documenting canopy-stratified deposition across key phenological stages i.e. tillering, booting, and heading in cereals such as rice and wheat, and prebloom to harvest in orchard systems along with operator-oriented decision charts, would provide critical resources for standardising UAV spray practices and improving field-level decision-making 8.4. Formulation science for UAVs Adjuvants that tune surface tension/viscosity consistently lift canopy deposition and biological control in rice; yet comparative data across chemistries, water qualities, and climates are sparse (Wang et al., 2024; Wongsuk et al., 2024). Priority actions: Head-to-head evaluations of adjuvant classes including methylated seed oils (MSO), methylated vegetable oils (MVO), crop oils, polymeric stickers, and drift retardants conducted at spray volumes relevant to UAV application have provided critical insights. These trials

establish mechanistic linkages between droplet size distribution, biological efficacy, and off-target drift potential (Wang et al., 2019; Zhou et al., 2020). 8.5. Aircraft and rotor–nozzle co-design Single-rotor vs. multirotor platforms, rotor count, and downwash profiles interact with nozzle type and swath to determine patterns. Evidence suggests single-rotor aircraft can improve uniformity in cereals, while octocopters boost penetration when paired with flat-fans and adjuvants (Wang et al., 2016; Wongsuk et al., 2024). Priority actions: A CFD informed co-design approach that simultaneously optimises rotor configuration and nozzle placement can enhance spray deposition efficiency. Field validation using continuous samplers coupled with residue extraction provides the necessary feedback to close the design performance loop. 8.6. Digital agronomy: sensing, autonomy, and IPM Future UAV programs should be data-driven: canopy height maps, wind fields, pest hot-spot scouting (multispectral/thermal), and adaptive path planning to vary height/speed/overlap on the fly (Velusamy et al., 2022; Subramanian et al., 2021). Priority actions: The integration of prescription maps with UAV flight controllers, combined with the coupling of scouting data to enable variable-rate spraying, offers a pathway for embedding UAV spraying within integrated pest management (IPM) frameworks. Such an approach, guided by economic thresholds and the preservation of refugia, has the potential to optimise input use while minimising ecological impacts. 8.7. Environmental safeguards and eco-metrics Low-volume UAVs can increase PUE and reduce operator exposure, but fine-droplet drift remains a concern in windy conditions. Standard drift fences and buffer guidance should be UAV-specific; ecological endpoints (non-target arthropods, aquatic edges) require dedicated trials (Zhou et al., 2020). Priority actions: Developing empirical drift-response curves as functions of flight height, speed, nozzle type, and adjuvant class, and concurrently reporting chemical load per unit of pest control as a sustainability metric alongside pesticide-use efficiency (PUE), would enable more holistic evaluation of UAV spray technologies 8.8. Economics and service models Evidence from Asia shows higher net returns, labour savings, and strong ICBR for drone tank-mixes; yet service availability and operator skill constrain scale (Ragiman et al., 2024; Pathak et al., 2020). Priority actions: Comparative assessments of ownership versus service-based economics, the feasibility of cooperative deployment models, structured training pipelines, and the logistical challenges of downtime including battery exchange and refill station requirements are critical for scaling UAV adoption in smallholder mosaic farming systems

8.9. Multi-pest, multi-objective programs UAVs excel for tank-mix programs that jointly manage insects and diseases (higher yields, better economics) (Ragiman et al., 2024). Beyond protection, nutrient and defoliant applications are promising (Nandhini et al., 2022; Liao et al., 2019). Priority actions: Designing season long spray programs that integrate both prophylactic and curative applications, optimising spray intervals and active ingredient rotations for resistance management, and validating downstream impacts on harvest outcomes and product quality, such as in almonds and cotton are essential for aligning UAV spraying with sustainable crop protection strategies 8.10. From trials to regulation Technical maturity must translate to regulatory acceptance: BMPs from industry (e.g., diamide guidance) offer a scaffold, but need public-domain

datasets and ISO-aligned dossiers to support label amendments (Li et al., 2019; Li et al., 2020). Priority actions: Pre competitive collaborations are needed to generate multi-site, multi-year datasets linking UAV spray efficacy, drift, and residue dynamics for priority crops such as rice, wheat, cotton, and orchards, thereby accelerating the development of UAV-specific pesticide labels. In sum, the research agenda pivots on standardisation, stage aware optimisation, formulation codevelopment, platform co-design, and data driven autonomy, all tied to regulatory-ready evidence. Addressing these priorities will convert the demonstrated field potential of UAV spraying into mainstream, sustainable crop protection. 9. CONCLUSIONS Over the past decade, UAV-based spraying has evolved from an experimental approach into a scientifically validated crop protection tool. Studies across rice, wheat, cotton, legumes, jute, and almond production systems have demonstrated that drones can achieve pest and disease control comparable to, and in some cases better than, conventional knapsack and air-blast sprayers (Qin et al., 2016; Li et al., 2020; Parmar et al., 2021). Enhanced pesticide-use efficiency (PUE), reduced spray losses, and improved canopy penetration due to rotor-generated downwash are among the major advantages associated with UAV spraying systems (Zhou et al., 2020). However, the effectiveness of UAV application is highly dependent on operational optimisation, including flight height, forward speed, nozzle configuration, spray volume, and adjuvant selection. Several studies have shown that crop stage-specific adjustments and canopy-based calibration significantly improve spray deposition and biological efficacy (Wongsuk et al., 2024; Wang et al., 2024; Weicai et al., 2023). Despite these advances, the absence of standardised methodologies for spray assessment remains a major challenge for regulatory acceptance and scientific comparison. Variations in collector materials, imaging software, and tracer quantification methods often generate inconsistent datasets. Recent studies suggest that combining Water Sensitive Paper (WSP)-based pattern analysis with extraction-based quantification techniques can provide more reliable evaluation of UAV spray performance (Ahmad et al., 2022; Koo et al., 2024). In addition to technical benefits, UAV spraying

requirements, lower pesticide consumption, minimised operator exposure, and improved profitability (Alam et al., 2024; Ragiman et al., 2024). Future progress will depend on stronger policy support, including UAV-specific pesticide regulations, operator certification systems, and development of standardised best management practices. Integration of drones with digital scouting, prescription mapping, and variable-rate application technologies is expected to further strengthen their role in sustainable integrated pest management (IPM) programmes. 10. REFERENCES Ahmad, F., Zhang, S., Qiu, B., Ma, J., Xin, H., Qiu, W., Ahmed, S., Chandio, F A., & Khaliq, A. (2022). Comparison of water sensitive paper and glass strip sampling approaches to access spray deposit by UAV sprayers. Agronomy, 12(6), 1302. Alam, M. Z. (2024). A Comprehensive Study of Historical Trends, Future Strategies, and Policy Recommendations for Energy Use in Bangladesh's Agriculture. Authorea Preprints. da Cunha, J. P. A. R., & da Silva, M. R. A. (2021). Deposition of spray applied to a soybean crop using an unmanned aerial vehicle. International Journal of Precision Agricultural Aviation, 4(2), 8-13. Gogolák, L., Simon, J., Pletikosity, Á., & Fürstner, I. (2024). Quantitative assessment of UAV assisted particle spraying distribution in agriculture: An image analysis approach using water sensitive papers. International Journal of Electrical and Computer Engineering Systems, 15(7), 553-562. Jing, L., & Wei, X. (2022). Spray deposition and distribution on rice as affected by a boom sprayer with a canopy-opening Device. Agriculture, 13(1), 94. Kaniska, K., Jagadeeswaran, R., Kumaraperumal, R., Ragunath, K. P., Kannan, B., Muthumanickam, D., & Pazhanivelan, S. (2022). Impact of drone spraying of nutrients on growth and yield of maize crop. International Journal of Environment and Climate Change, 12(11), 274-282. Koo, D., Henderson, C. A., & Askew, S. D. (2024). Agricultural spray drone deposition, Part 1: methods for high-throughput spray pattern analysis. Weed Science, 72(6), 816-823. Lan, Y., Qian, S., Chen, S., Zhao, Y., Deng, X., Wang, G., Zang, Y., Wang, J., & Qiu, X. (2021).

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The Future of Farming: Agricultural Drone Spraying in India Narayanaswamy Jeevan1*, Anil K2, Veershetty3, Surla Pradeep Kumar4 and Yerradoddi Sindhu Sree5 1,4,5

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ABSTRACT The agricultural sector in India is on the brink of a technological revolution, driven by the adoption of drone spraying technology. This innovation offers significant benefits, including enhanced precision, efficiency, and sustainability in crop management. This article explores the transformative impact of drone spraying on Indian agriculture, highlighting its advantages, current applications, challenges, and future potential. By examining recent scientific studies and advancements, we provide a comprehensive overview of how drone technology is reshaping farming practices and contributing to a more productive and environmentally friendly agricultural sector. INTRODUCTION

I

n recent years, India’s agricultural sector has seen a dramatic transformation, thanks to advancements in technology. Among

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these innovations, agricultural drone spraying is rapidly gaining traction. This technology promises to revolutionize farming practices,

offering improved efficiency, precision, and sustainability. This article provides the insights into the benefits, current state, and future of drone spraying in Indian agriculture, drawing on recent scientific research to highlight its potential impact. 1. The Emergence of Drone Spraying Technology

Moreover, drones significantly improve efficiency, which can cover up to 20 hectares in a single day, a feat that would take several days with manual spraying methods. This efficiency is particularly beneficial for largescale farms, where timely application of chemicals is crucial for maximizing crop production (Patel et al., 2023). 2.2. Labor and Cost Savings

Agricultural drones, equipped with advanced spraying systems, are becoming a gamechanger for farmers across India. Traditionally, crop spraying has been labor-intensive and time-consuming, often requiring significant manpower and resulting in uneven application of pesticides and fertilizers. Drones offer a modern solution to these problems, providing a more efficient and accurate method of crop management.

Labor shortages are a persistent issue in agriculture, and drone technology offers a solution. By reducing the need for manual labor in spraying, drones can lead to substantial cost savings. Sharma et al. (2024) highlight that using drones for crop spraying can decrease labor costs by up to 40%, making it a cost-effective alternative to traditional methods. Additionally, drones eliminate the need for expensive manual application equipment, further lowering operational costs. 2.3. Environmental Benefits

- Key Advantages of Drone Spraying

Environmental sustainability is a major concern in agriculture, and drones help address this by reducing chemical runoff and overuse. Gupta et al. (2023) explain that drone spraying contributes to more sustainable farming practices by applying chemicals more accurately and minimizing the risk of environmental contamination.

2.1. Precision and Efficiency

2.4. Enhanced Crop Health Monitoring

One of the most notable advantages of drone spraying is its precision. Drones can deliver pesticides and fertilizers with pinpoint accuracy, reducing the risk of over-application and minimizing waste. This precision not only enhances crop health but also contributes to environmental sustainability. Drones can cut pesticide use by up to 30% while maintaining or even boosting crop yields. This level of accuracy is difficult to achieve with traditional spraying methods, which often lead to uneven coverage and higher chemical use.

Drones are not only useful for spraying but also for monitoring crop health. Drones can detect early signs of pest infestations, nutrient deficiencies, and diseases, which were equipped with high-resolution cameras and sensors. This early detection allows for timely interventions, reducing the risk of widespread crop damage. Kumar et al. (2022) emphasize that integrating drone-collected data with precision agriculture practices can lead to more effective crop management and improved yields.

Figure 1. Spraying of agro-chemicals using Hexa-copter drone in the paddy field

2.5. Data Integration and Decision-Making

3.3. Technical Training

The data collected by drones can be analyzed to gain valuable insights into crop health and environmental conditions. This data can be integrated with other farm management systems to develop comprehensive strategies for optimizing crop performance. Sharma et al. (2024) notes that combining drone data with soil and weather information allows farmers to make informed decisions about irrigation, fertilization, and pest control, ultimately leading to better resource management.

Effective use of drones requires specialized knowledge and skills. Farmers need training to operate drones and interpret the data they collect. To address this need, training programs and workshops are being organized to educate farmers on drone technology and its applications in agriculture.

- Challenges and Solutions Despite its advantages, the adoption of drone technology in Indian agriculture faces several challenges. These include regulatory hurdles, high initial costs, and the need for technical training. 3.1. Regulatory Hurdles Navigating the regulatory framework for drone use in India can be complex. Although the government has introduced guidelines to facilitate the use of drones in agriculture, farmers and businesses may encounter difficulties in obtaining necessary licenses and approvals. Recent efforts by the Indian government aim to streamline these regulations, making it easier for farmers to adopt drone technology. 3.2. High Initial Costs The initial investment required for purchasing drones and related equipment can be substantial, particularly for smallholder farmers. To address this barrier, the Indian government and various organizations are offering subsidies and financial assistance to support drone adoption. Additionally, as technology advances and becomes more widespread, the cost of drones is expected to decrease.

- The Future of Drone Technology in Indian Agriculture The future of drone technology in Indian agriculture looks promising. As the technology continues to evolve, drones are expected to become an integral part of farming practices, enhancing productivity and sustainability. Ongoing research and development are focused on improving drone capabilities, reducing costs, and expanding their applications in agriculture. India is on the brink of a technological revolution in farming, with drone spraying at the forefront. By addressing current challenges and leveraging the benefits of drone technology, Indian agriculture can achieve greater efficiency, sustainability, and productivity. CONCLUSION Agricultural drone spraying represents a significant advancement in farming technology, offering numerous benefits including precision, efficiency, labor and cost savings, environmental sustainability, and improved crop health monitoring. As India continues to embrace this technology, it has the potential to transform the agricultural landscape, addressing longstanding challenges and paving the way for a more sustainable and productive future. As drone technology continues to advance, it promises to usher in a new era of precision farming in India, offering farmers innovative tools to enhance productivity and sustainability.

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Article

Pesticide Exposure of Operators from Drone Application: A Field Study with Comparative Analysis to Handheld Data from Exposure Models Christian J Kuster,* Maxie Kohler, Sarah Hovinga, Christian Timmermann, Georg Hamacher, Kathrin Buerling, Lirong Chen, Nicola J. Hewitt, and Thomas Anft Cite This: ACS Agric. Sci. Technol. 2023, 3, 1125−1130

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ABSTRACT: Operator exposures to pesticides of mixer/loaders (M&L) and pilots during drone application in a typical paddy rice field were measured using a tracer formulation. Median potential dermal exposures to M&L and pilot operators were 9.886 and 0.400 mg substance/kg substance handled, respectively, indicating that operator exposure was mainly during M&L (with 73% detected on the operator’s hands). M&L operator exposure was reduced by 21% by wearing one layer of certified clothing (to 7.817 mg/kg), and by a further 98% by also using Tyvec gloves (to 0.173 mg/kg). Potential and actual exposures of drone pilots were 0.400 and 0.012 mg/kg, respectively. When 75th percentiles were compared to those from publicly available handheld exposure models recommended for regulatory purposes, the use of drones for application resulted in an exposure reduction of 90−99%. In conclusion, compared to handheld spray equipment, the use of drones for pesticide application significantly reduces the operator exposure. KEYWORDS: operator exposure, residues, plant protection products, drone application, mixing and loading, unmanned aerial spray systems

- INTRODUCTION Drones, or unmanned aerial spray systems (UASSs), are increasingly used for agricultural pesticide applications and have the potential to provide numerous benefits to the environment and human health and improve the operational efficiency of the farm. UASS can be used in difficult conditions that would otherwise be hard to access for manual labor such as steep vineyards or flooded rice fields, thus greatly improving labor conditions and efficiency.1 In addition, in the context of precision agriculture, they can also positively contribute to climate and sustainability goals.2 In the area of operator safety, the use of drones has the potential to greatly reduce applicator exposure, specifically in agricultural procedures that primarily rely on handheld application devices, which are still the predominant application methods in low- and middle-income countries.3 Instead of being physically present in the field being treated, a drone operator is operating from a distance. Since the use of drones is a more efficient and safer way to apply pesticides, it is becoming more popular as the technology and its availability improve.4 Asia leads the way in adopting drone technology for pesticide application, with countries such as Japan, China, and Korea showcasing significant advantages over traditional methods. The rapid advancements in integrating this technology into agricultural regulations further attest to its efficacy and potential.5 While the potential benefits are clear, there are still areas and specific scenarios that require further study and proof to ensure the safe and effective use of UASS for agricultural applications. For example, one area that warrants further investigation is how exposure during drone © 2023 The Authors. Published by American Chemical Society

pesticide application procedures, such as mixing and loading (M&L), product application, battery changes, and handling of the drone itself, potentially differ from conventional pesticide application methods where the risks have been well-studied and characterized.6−8 It is important to characterize human safety for pesticide applications in a risk-based approach to ensure that operators are adequately protected from the potential health risks associated with pesticide exposure.9 The risk assessment for operators is based on the hazard of

the pesticide itself, as well as the exposure of the operator, which considers the specific use pattern including application technology, crop characteristics, product concentration, vortex strength, spraying altitude, layout of nozzles and rotors, atomization, downwash airflow, and autonomous navigational controllers. Additionally, proper personal protective equipment (PPE), specifically chemicalresistant gloves, can often be used to minimize the potential exposure risks to M&L operators (e.g., Lee et al.10). The majority of exposure studies have shown that the main exposure during M&L is on the hands; hence, chemical resistant gloves are the most efficient in significantly reducing exposure. However, other types of PPE can also reduce Received: July 27, 2023
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the study. We determined both potential and actual exposure (factoring in the use of protective workwear) to a wettable powder (WP) tracer formulation diluted in water as a surrogate for a pesticide. A key aspect of this study, which is lacking in previous reports, is that it captures photographic and quantitative details of the exposure to operators during the mixing process of the product with water, the loading of the dilution into the drone, the exposure to the drone pilots during application and battery changes, as well as the cleaning procedure after the operation was completed. Potential exposure refers to the theoretical contact an individual may have with a substance under specific conditions without accounting for protective measures. Actual exposure represents the real contact a person has with the substance, considering the protective measures employed such as workwear. Results were compared with published exposure data models for handheld uses to identify any procedures specific to drone pesticide applications that could result in potentially increased exposure.

- MATERIALS AND METHODS Details of the study, which was in accordance with Organization for Economic Cooperation and Development (OECD) guidance No. 9,15 together with photographs of equipment and operator steps, are described in the Supporting Information. Information includes the study location (Supplementary Figure S1 and Supplementary Table S1), drone types, and specifications (Supplementary Figure S2 and (Supplementary Table S2)), details of the tracer (Supplementary Table S3), operator task descriptions (Supplementary Figure S3 and S4 and Supplementary Table S4) and operator clothing (Supplementary Figure S5), as well as the sampling (Supplementary Figure S6 and Supplementary Table S5) and analytical methods for the tracer substance in the various samples collected (field spike samples (Supplementary Figure S7 and Supplementary Table S6 and S7)). The operator exposure study was performed in the Sri Prachan District of Suphanburi Province in Thailand. Briefly, the study used a total of 12 operator measurements using six drones and two drone types (both representative of this type of use and a tracer substance, Brilliant Blue G, as the test substance. M&L operators prepared the spray solution and then transferred it to the drone's tank. This procedure was conducted multiple times (the frequency per operator was between a range of 17 and 23 times for all operators) during the application phase. The drone was operated by a drone pilot operator using a remote control to spray the crop with the tracer substance. At the end of the daily task, the drone was cleaned. Workers wore normal work attire during M&L and application. In addition, protective impervious coveralls (Tyvek) and protective gloves while cleaning the drone. Skin exposure was further assessed by wearing 100% cotton long-sleeved T-shirts and long johns, while hand exposure was determined using chemical-resistant nitrile gloves and hand washings, and head exposure was determined via face/neck wipes. Inhalation exposure was also determined via Institute of Occupational Medicine (IOM) samplers connected to pumps running at 2 L/min. However, due to insufficiently low-field spike recoveries, the values were considered not reliable. In addition, nondietary exposure and risk assessments for agrochemicals in the European Union (EU) consider the dermal route as the primary exposure pathway for operators, bystanders, residents, and re-entry workers.9,16 Potential dermal exposure was calculated as the sum of residues on outer dosimeters (jacket and trousers), protective

nitrile gloves, inner dosimeters, hand washes, and face and neck wipes. In addition, residues on impervious clothing (Tyvek) during the cleaning process were measured and included in the calculation of the potential dermal exposure. This is intended to represent dermal exposure to a person when there is no protection from clothing. Actual dermal exposure was calculated as the sum of inner dosimeters, hand washes, and face neck/wipes. This is intended to represent dermal exposure to a person 1126

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exposure but to other body parts, e.g., the use of a working coverall is recommended according to good agricultural practice. Operators can reduce exposure to the body further by wearing an apron or even impervious clothing such as Tyvek. Very often, the use of an FFP1/FFP2 (Filtering FacePiece) mask is perceived as the most impactful PPE for operators. However, this is often not the case because exposure via inhalation is negligible when products are formulated as liquids or as water-dispersible granules. Inhalation exposure is significant only when the product is formulated as a powder, which can be mitigated by wearing a filter mask. Notably, the highest exposure of powders is also to the hands; therefore, wearing (nitrile) gloves is the best way to reduce exposure and protect operators. With respect to the risk assessment using UASS technology, the lacking data are primarily related to exposure, efficacy, and drift.7 Characterizing potential human safety risks, especially in the case of a new application method, such as with drones, can help to ensure that operators are properly trained and have the right safety equipment in place to reduce the risks associated with handling and applying pesticides. A recent review of the literature identified very little empirical data and information on levels of operator exposure resulting from the use of UASS has been published.7 Moreover, the American Society of Agricultural and Biological Engineers (ASBAE) and ISO activities to date have not focused on traditional regulatory studies for operator exposure to pesticides. Instead, the ASABE makes recommendations for operator certifications by aerial regulatory authorities (FAA), drone machinery, specifications, classifications, sensing, and best management practices,11 and the ISO guidance relates to the standardization, classification, design, manufacture, operation, and general safety management.12 Therefore, more understanding of the methodology and data generation is needed to investigate the impact of their use on operator exposure. Some job steps involved in pesticide application with drones, such as M&L may be similar to conventional methods, especially for ones that involve smaller tank sizes, as is the case with handheld applications using a backpack. However, other unique job steps mentioned earlier may need further characterization. Residues on the drones could occur during application since the turbulent flow from drones is complex and potentially unique from other application types, especially with multi-rotor devices.13 Additionally, as operators may lift the UASS by their arms, wearing PPE, as required on product labels, is important. The potential of increasing risk of sensitization or irritation from using high product concentrations due to the relatively low carrying capacity of a UASS is another area to be considered. Indeed, low-volume formulations specifically designed for drones are a field of study still under development by pesticide manufacturers. Literature searches identified only one study by Yan et al.14 in which operator exposure was measured during drone application, which was compared with exposure during handheld application. Therefore, further information would help establish a baseline of comparison. The aim of this study was to determine operator exposure to pesticides in a typical agricultural drone application scenario in Thailand, Asia. Rice was selected as a test crop for the exposure assessment because it has become the most common commercial crop for drone application in the region. Additionally, widely used octocopters commercial DJI MG1S and 1P model drones with four nozzles were employed in

wearing one layer of typical work clothes, including gloves. The reduction by one layer of certified clothing was calculated according to eq 1: (Potentinal exposure Actual exposure) × 100 Potential exposure (1) The % reduction of actual exposure by adding gloves in addition to certified clothing was calculated according to eq 2:

%Reduction = (Actual exposurew/ogloves Actualexposure + gloves) Actual exposurew/ogloves (2)

The predicted operator exposure for occupational exposure to the tracer substance for application using handheld backpacks was calculated using the Agricultural Operator Exposure Model (AOEM),6 the Bayer Safety

Standard model,17 as recommended by the OECD,1 and the CropLife OPEX Tool (CLI),8 as recommended by the FAO.18

- RESULTS The individual exposure results for each operator are presented in Supporting Information Tables S8−S11. Our results indicate that the M&L task is the main driver of dermal exposure compared to exposure for the drone pilot applying the product (Figure 1). The median value for potential
- DISCUSSION The data from this study show that the use of drones to spray pesticides reduces operator exposure significantly when compared to hand-held devices: Drone application can reduce applicator exposure by more than 99%, reducing the need for additional PPE in this case, such as impervious clothing during backpack application where the operator is colocated with the pesticide application. This is particularly beneficial in countries with hot and humid climates where wearing nontranspiring clothing can pose a challenge and contribute to undesirable working conditions. These results indicate that the M&L task is the main driver of dermal exposure compared to exposure for the drone pilot applying the product. During M&L of the surrogate powder formulation, visible residues on operators' clothing were apparent (see Supporting Information, Figure S6), and later were confirmed by sample analysis. The electrostatic nature of particles is well-known, with synthetic clothing materials being more susceptible to static charge generation, increasing the likelihood of particle adhesion, particularly for very fine powders. The use of a liquid or a water-dispersible granule formulation would most likely further reduce potential and actual exposure during the M&L process. The determination of

Figure 1. Comparison of the potential exposure to M&L versus pilot operators and the impact of PPE on exposure. Individual values are shown, together with the median, highest and lowest values (error bars, without outliers (which are automatically calculated by the graph software but are included in the statistical anaylsis)), 25th and 75th percentiles (bottom and top of the blue whisker boxes) for normalized M&L exposure (mg/person/kg handled/day) for [1] estimate for a potentially naked operator (potential), [2] assuming one layer of certified clothing without any protective gloves (actual exposure), [3] assuming one layer of certified clothing and chemical resistant gloves, and [4] potential exposure of the pilot. Red arrows with percentage values show the average decrease of exposure with the indicated additional PPE.

exposure to the M&L operator was 9.886 mg substance/kg substance handled, whereas the median potential exposure to the pilot operator was 0.400 mg substance/kg substance handled. For pilot operators, one layer of clothing and protective gloves were worn at all times, including when handling contaminated surfaces (due to residues being on the drones themselves due to, e.g., drift), representing the scenario 1127

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of "actual exposure with protective gloves"; however, potential exposure is shown in the figure as a worst-case scenario. The measured exposure of the M&L operator is reduced from the median potential exposure of 9.886 mg/person/kg handled/day by 21% with the addition of one layer of certified clothing (actual exposure: 9.167 mg/kg). Actual exposure is further decreased by 98% by wearing gloves in addition to certified clothing (actual exposure with gloves was 0.173 mg/ kg). This results in an exposure of the M&L operator when assuming work wear and protective nitrile gloves which is similar to the potential and actual exposure of the drone pilot (0.3996 and 0.287 mg/person/kg handled/day, respectively). With regard to the outer clothing exposure, most of the residues for the M&L task are detected on the gloves (78% of total outer exposure) and on the upper body area (18%) with minimal relative residues recovered from the lower body (4%) (Figure 2). The levels of protection of one layer of certified clothing and gloves were 96% and 99.5%, respectively. The measured exposure values under the protective clothing were therefore all relatively low (green symbols in Figure 2). Additionally, we measured potential exposure explicitly for the cleaning process by analyzing impervious clothing (i.e., Tyvek) that was used only for the cleaning process. This showed that residues on that Tyvek were low, indicating that the cleaning process itself does not result in extraordinarily higher exposure (gray symbols in Figure 2). To estimate the exposure reduction for the applicator in a backpack/handheld scenario compared to a drone pilot scenario, data from this study (75th percentiles) were compared to handheld exposure models that are recommended by the FAO pesticide registration toolkit18 (the AOEM and CLI models) or listed in the OECD list of exposure models (the Bayer Safety Standard model) (Figure 3, see Supporting Information Figure S8 for the calculations of exposure). Compared to backpack or general handheld equipment, the use of drones

generally resulted in an exposure reduction of over 90%. For potential exposure, the reduction achieved using drones compared to handheld for application is even more pronounced, with more than 99% in each scenario.

%Reduction =

× 100

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Figure 3. Comparison of applicator exposure using drones with backpack/handheld devices and percentage reduction in exposure due to the use of a drone. Normalized pilot operator exposure (mg/person/kg handled/day, indicated as numbers and visually using the red bars) is shown for potential exposure, assuming one layer of certified clothing (actual exposure, no gloves) and, in addition, wearing chemical resistant gloves (actual exposure with gloves) compared to publicly available data from exposure models like the AOEM (Großkopf et al., 2013), the Bayer Safety Standard model,17 as recommended by the OECD,1 and the CLI, as recommended by the FAO.18 Values for the 75th percentiles were compared. The % reduction was calculated using the values shown.

inhalation exposure would have brought additional value to this study, in particular during the M&L process. While inhalation exposure to liquids is typically negligible, inhalation exposure to WP, as used in the present study, is often much

higher. However, due to inconsistent results obtained for the IOM-sampler field spike samples for which no explanation could be found operator IOM-sampler results were excluded from a further evaluation regarding operator inhalation 1128

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Figure 2. Normalized M&L exposure (mg/person/kg handled/day) for the different parts of the body. [1] = indicates the exposure during cleaning the drone with a Tyvek suit that is worn on top of normal work clothing, [2], [3], and [4] = represent residues on outer clothing on the upper part of the body, lower part of the body, and gloves, respectively, and [5], [6], and [7] = indicate skin exposure under protective clothing. The circle indicates the distribution of exposure on hands (including gloves) upper and lower part of the body.

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exposures. Nevertheless, our procedure for M&L (the powder was diluted with water and then transferred to the drone with a watering can) is realistic and reflects a common practice in the field, particularly in Asia. However, our results demonstrate that potential exposure during M&L can be significantly reduced by wearing the proper PPE of protective clothing and gloves, as with any conventional M&L operation. One other study by Yan et al. that is available on operator exposure during drone application showed similar results. Their measurements also demonstrated a significant reduction (>90%) in exposure during drone application compared to handheld devices. However, it should be noted that the absolute exposure reported by Yan et al. was remarkably higher compared to our study results, which was conducted according to OECD standard procedures, possibly due to different application methods. In their study, the operator used knapsacks, sprayed the pesticide upward, and walked directly through the pesticide mist, which is not necessarily in accordance with good agricultural practice.19 Another possible explanation for the higher residues on clothing and skin in the study of Yan et al. could be that the sampling methodology combined M&L and application job steps, while in our study, these tasks were analyzed separately. Another consideration regarding the comparison of drones and handheld devices is the manner in which the exposure reduction data are expressed. In our comparison, we normalized exposures to the amount of substance sprayed (i.e., mg per kg a.i. handled), which is the best way to compare different models and application methods. However, most handheld devices are limited to a treated area of 1 ha/day due to the physical nature of the task, but treated areas can be considerably higher when drones are used. This means that the difference in total exposure from a day's spraying with a drone or a

backpack may not be as great as the difference between the normalized values. It is worth noting that while our study shows reduced exposure of pesticides with drones compared to backpack sprayers, more studies are needed to fully understand human safety elements of drone pesticide applications, for instance, studies that investigate in airborne spray drift downwind of the target area to assess potential bystander and resident exposure, which is an important consideration for any pesticide application method. A recently published study by Dubuis et al.20 aimed to quantify the environmental, residential, and bystander exposures following drone application in an orchard under field conditions. Their findings demonstrate that the drift deposit levels observed for the specific drone used are covered by current regulatory models relating to the drift of orchard sprayers. The development of best management practices that include all elements related to safe and legal operations of drones would benefit users and bystanders. In addition, it would be beneficial to understand local differences in drone uses by receiving more information on drone types, e.g., loading per day, area covered, and type of crop. With this information, further studies could be conducted to estimate operator exposure under varying conditions. In conclusion, our study confirms the benefits of using drones for pesticide application by reducing the exposure of pilot operators while acknowledging the need for further research to confirm the effectiveness of the procedure in reallife applications. Our results also demonstrate the importance of wearing protective clothing and gloves by operators, especially during M&L activities. This study suggests that

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drone application can be an effective alternative to traditional handheld spraying methods. Additionally, the use of drones for pesticide application offers other benefits, including reduced time spent applying with handheld devices, improved working conditions which attract a larger labor pool, and the ability to apply even when one cannot enter the field due to muddy conditions. As drone technology continues to advance, we may see new uses for drones in pest management, offering a more sustainable and efficient way to manage crops.

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ASSOCIATED CONTENT

s1 Supporting Information *

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsagscitech.3c00253.

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ABBREVIATIONS AOEM, Agricultural Operator Exposure Model; PPE, personal protective equipment; WP, powder formulations; UASS, unmanned aerial spray systems 1129

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Details of the study; tabular and photographic details and descriptions regarding information on the study; location; details of the tracer; drone types, specifications and operation; operator clothing and task descriptions; dermal sampling procedures; analytical methods (analysis, field recoveries) for the tracer substance in the various samples collected; calculations of predicted exposure for M&L using a hand-held backpack; measured results for each operator; and calculated exposures using the Bayer Safety Standard, AOEM, and CLI models. (PDF)

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case study 2

Etherealflights

Drone Spraying in Indian Agriculture Case Studies & Measured Benefits Accelerating precision crop care in India India-focused case studies | Quantified outcomes | Regulatory-ready operations

2026-02-26 | Confidential Presentation

Why Drone Spraying for India – The Context

Fragmented Landholdings 86% of Indian farmers operate on less than 2 hectares. Small, irregular plots and wet paddy fields limit heavy machinery access, making drones the ideal aerial solution.

Etherealflights

95%

Labor & Safety Crisis Acute labor scarcity during peak seasons drives up costs. Manual backpack spraying causes heat stress and severe chemical exposure for operators.

Key Advantages Faster coverage (20x vs manual) Reduced operator exposure Access to waterlogged fields

Critical Timing Windows

Better chemical uniformity

Narrow windows for pest/disease control in paddy, cotton, and horticulture require rapid coverage that manual labor cannot match.

Precise spot spraying capability

India Context Overview

2026-02-26

How We Measured Benefits

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Standardized metrics for evaluating drone performance vs. conventional methods

Throughput

Water Volume

Speed of coverage compared to manual labor. Critical for narrow disease control windows.

Drastic reduction in water usage, solving logistical challenges in water-scarce regions.

ha/hr | acres/day | min/acre

L/ha | L/acre

Efficacy & Coverage

Economics Cost comparison for farmers and ROI potential for service providers.

% Control | Drops/cm²

₹/acre Custom Rate | ROI

PJTSAU SOP Trials (2024)

Reduction in active ingredient usage while maintaining efficacy (within label compliance). % Change vs. Label/ Manual

Pest/disease control incidence and droplet density on target surfaces.

Verified Data Sources

Chemical Use

KVK Field Demonstrations

Drift & Safety Off-target movement analysis and operator exposure reduction levels. Buffer Distance | Exposure Risk

State Agriculture Dept. Reports

FPO Pilot Service Logs

Case Study: Punjab (Paddy)

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Faster, Safer, Lower Water Usage in Waterlogged Fields

Trial Setup & Context Location: Punjab, Kharif Paddy Season Equipment: Multi-rotor UAV (30–40 kg class) Parameters: 8–10 L/acre volume, coarse-medium droplets

Water Usage

95% 200L → 10L/acre

Time Efficiency

4x 30 min → 7 min/acre

Cost Benefit

Drone operation over mature paddy field in Punjab

~25% ₹800 → ₹600/acre

Key Implications for Farmers Timely Window Spraying Rapid coverage ensures disease control even in waterlogged fields where laborers struggle to walk.

Farmers verifying coverage with water-sensitive paper

Case Study: Maharashtra (Mango Orchards)

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Canopy Coverage on Slopes: Konkan & Western Ghats

Conventional Airblast

Lower Leaf Deposition Improvement

Drone Spraying

WATER VOLUME

WATER VOLUME

800–1,000 L/ha

30–50 L/ha

COVERAGE UNIFORMITY

COVERAGE UNIFORMITY

Variable

+35% Deposition

Poor on upper canopy & inner leaves

Superior lower-leaf & inner canopy penetration

FIELD IMPACT

FIELD IMPACT

High Impact

Zero Impact

Heavy soil compaction & tractor ruts on slopes

VS

95%

Aerial application eliminates soil damage

ACCESSIBILITY

ACCESSIBILITY

Limited

100% Access

Cannot reach steep/terraced zones

Easily covers steep, terraced, & irregular plots

Operational Implications Access to steep terrain: Drones successfully sprayed terraced orchards previously accessible only by hand labor. Reduced runoff: Ultra-low volume application minimizes chemical runoff into water bodies in high-rainfall zones. Canopy penetration: Downwash from rotors pushes droplets deep into dense mango foliage for better pest

Case Study: Karnataka Vegetables

Etherealflights

Spot & Block Sprays in Chili/Tomato

Trial Setup & Context Location: Northern Karnataka (Chili/Tomato) Method: Prescription maps for hotspot sprays Parameters: 10–20 L/ha variable rate application

Labor Reduction

Water Savings

Coverage

40%

95%

25 ac

vs knapsack teams

Drastic volume cut

Per day across plots

Drone operation over chili plantation in Karnataka

Key Implications for Farmers Resistance Management Timely interventions prevent pest buildup and reduce chemical resistance.

Farmers inspecting crop health post-spray

Case Study: PJTSAU Rice SOP Trials (Telangana)

Etherealflights

Standardized Protocol Validation & Impact Assessment

Key Findings Pesticide Reduction: Achieved 15–20% reduction in active ingredient usage compared to conventional aerial/ground spraying while maintaining label compliance. Optimized Volume: Validated ~30 L/ha as the optimal UAV spray volume for consistent coverage without runoff. Efficacy Parity: Demonstrated on-par pest control efficacy with managed drift through controlled droplet size and flight height.

15-20%

30 L/ha

Chemical Reduction

Optimal Spray Volume

Source: PJTSAU Standard Operating Protocols for Drone Pesticide Application in Rice (2024)

Pesticide Application Comparison (a.i. per ha)

Case Study: KVK Shajapur (Madhya Pradesh)

Etherealflights

Paddy/Soy Demo: Custom Hire Viability & Water Savings

Trial Setup & Context Location: Shajapur, Madhya Pradesh (Paddy/Soybean) Method: UAV demo with water-sensitive paper validation Focus: Time-motion study & water volume comparison

Speed / Throughput

Water Efficiency

~10 min

95%

Per Acre Coverage

200L → 10L/acre

Custom Rate

KVK demonstration of drone spraying technology in MP

₹500-600 Per Acre (Typical)

Key Implications for Custom Hiring Viable Business Model Proven unit economics supports rural entrepreneurship and custom hiring centers (CHCs).

Farmers evaluating spray coverage efficiency

Case Study: Andhra Pradesh (Paddy)

Etherealflights

Throughput & Input Savings: Coastal AP (Tillering-Booting Windows)

Manual Knapsack

Drone Fleet

THROUGHPUT / CAPACITY

THROUGHPUT / CAPACITY

~0.15 ha/hr

2.6 ha/hr

Labor-intensive, slow coverage

~17x faster coverage speed

WATER USAGE

WATER USAGE

200–300 L/ha

10–15 L/ha

High water requirement

95% water saving achieved

VS CHEMICAL INPUT

CHEMICAL INPUT

100% Standard Rate

75% of Std Rate

Standard label dosage applied

25% reduction (SOP-guided)

RESPONSE TIME

RESPONSE TIME

Slow (Days)

Rapid (Hours)

Critical delays during pest outbreaks

Immediate response capability

Operational Efficiency Gains

Strategic Implications Cyclone-Window Spraying: Rapid coverage capability allows entire village clusters to be treated during short windows before/after cyclones.

FPO Fleet Potential: High throughput (2.6 ha/hr) validates the economic model for Farmer Producer Organizations to own custom hire fleets. SOP-Guided Savings: Protocols allowing 25% chemical reduction maintain efficacy while significantly lowering input costs for farmers.

Case Study: Tamil Nadu Herbicide Trial

Etherealflights

UAV vs. Knapsack: Comparative Analysis in Rice/Maize Plots

Trial Outcomes

Water Volume & Application Efficiency Comparison

Optimized Application: Comparable weed control efficacy achieved with 30 L/ha UAV volume versus 500 L/ha knapsack volume, matching AI rates. Operational Efficiency: Validated optimal flight parameters of 23m AGL altitude with Coarse droplet spectrum for drift management. Safety & Soil Health: Significant reduction in operator chemical exposure and minimization of soil compaction compared to manual walking.

94%

2-3m

Water Savings (30L vs 500L)

Optimal Flight Altitude (AGL)

Source: TNAU/PAJANCOA Field Trials & Extension Proceedings (2024-2025)

Case Study: KVK Vriddhachalam (Tamil Nadu)

Etherealflights

Unit Economics for Rural Custom Hiring Centers

Operations Snapshot Location: Cuddalore District, Tamil Nadu Crew: 1 Pilot + 1 Visual Observer (VO) Asset Utilization: 1 Drone + 3-4 Batteries + Fast Charger

Daily Capacity

Service Rate

Efficiency

30 acres

₹600 /acre

10 min

Optimized logistics flow

Range: ₹500 - ₹600

Per acre turnaround

Certified pilot managing operations during peak season

Business Implications Viable Rural Entrepreneurship Clear unit economics allow rural youth to operate profitable custom hiring centers with minimal overhead.

Drone deployed for multi-crop spraying service

Operate Responsibly: Evidence-Based Cautions

Etherealflights

Compliance, Safety & Standards in the Indian Context

Label Compliance

Drift Management

Pilot Training

CIB&RC Regulations

Critical Operational Standard

DGCA Requirement

Aerial Labeling: Use only products/crops approved for aerial application by CIB&RC.

Flight Parameters: Maintain low flight height (1.5–2.5m above canopy) per SOPs.

RPTO Certification: All pilots must be trained and certified by DGCA-approved RPTOs.

State Advisories: Strictly follow local agricultural university (SAU) and state dept. guidelines.

Droplet Size: Ensure appropriate nozzle selection (Medium/Coarse) to minimize fines.

Airspace Rules: Adhere to Green/Yellow/Red zone restrictions (Digital Sky platform).

Buffers: Respect buffer zones near water bodies, aquaculture, and bee boxes.

UIN Registration: Ensure all drones have Unique Identification Numbers (UIN).

Dosage Adherence: Maintain prescribed active ingredient rates; do not under-dose.

Documentation Operational Safety

Best Practice

Standard Operating Procedure

PPE Mandatory: Full PPE for mixing/loading crew to prevent exposure.

Decontamination: Strict tank cleaning and triplerinse waste disposal.

Battery Safety: Proper storage and charging protocols to prevent fire hazards.

Emergency Plan: First aid kit and emergency contacts readily available on site.

Flight Logs: Maintain detailed mission logs (area, time, product). Traceability: Record chemical batch/lot numbers for every application.

Etherealflights Rollout Plan – India

Etherealflights

Strategic Implementation Roadmap: Service, Compliance & Operations

PHASE 1

PHASE 2

PHASE 3

PHASE 4

PHASE 5

Service Model

Compliance

Operations

Data & Tech

Partnerships

Custom hire rates: ₹500– 700/acre based on crop & terrain

UIN/UAOP registration for all fleet drones

Standardized battery/generator kits for field autonomy

Digital flight logs & input volume tracking

Seasonal bulk packages for Farmer Producer Organizations (FPOs) Subscription models for high-value orchard management

Etherealflights Strategic Roadmap

DGCA RPTO partnerships for pilot certification Strict adherence to statespecific SOPs & CIB&RC guidelines

Mobile water bowsers & field mixing protocols Spare parts inventory management for rapid repair

Client dashboards for spray verification & billing Deposition card analysis for quality assurance

Collaborations with KVKs & State Ag Departments Financial tie-ups with banks/NBFCs for operator loans Insurance providers for crop & drone coverage

2026-02-26

ROI Snapshot & Next Steps

Etherealflights

Financial Viability & Implementation Roadmap

Strategic Next Steps

25-35

900-1,200

₹550

ACRES/DAY CAPACITY

BREAKEVEN ACRES

TARGET RATE/ACRE

1

Pilot Clusters Launch Initiate operations in Punjab, Telangana, Karnataka, and Tamil Nadu high-density zones.

2

KVK Joint Trials Co-run efficacy validation trials with local Krishi Vigyan Kendras for farmer trust.

Breakeven Analysis (Season) 3

Operator Financing Partner with banks/NBFCs for drone financing packages for rural entrepreneurs.

Book a Field Demo

Enroll as Operator

Source: `case_study_2.pdf` · Google Drive file id `1F4DXH29RydEjrBxPcseQ_v5OEb1kactF` · folder “8. Agricultural University Research”

drones-08-00296

drones Review

Artificial Intelligence Applied to Drone Control: A State of the Art Daniel Caballero-Martin 1,2 , Jose Manuel Lopez-Guede 1,2, * , Julian Estevez 1,3 1

2

3

4

*

and Manuel Graña 1,4

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Abstract: The integration of Artificial Intelligence (AI) tools and techniques has provided a significant advance in drone technology. Besides the military applications, drones are being increasingly used for logistics and cargo transportation, agriculture, construction, security and surveillance, exploration, and mobile wireless communication. The synergy between drones and AI has led to notable progress in the autonomy of drones, which have become capable of completing complex missions without direct human supervision. This study of the state of the art examines the impact of AI on improving drone autonomous behavior, covering from automation to complex real-time decision making. The paper provides detailed examples of the latest developments and applications. Ethical and regulatory challenges are also considered for the future evolution of this field of research, because drones with AI have the potential to greatly change our socioeconomic landscape. Keywords: artificial intelligence algorithms; drones; cargo transport; autonomous decisions Citation: Caballero-Martin, D.; Lopez-Guede, J.M.; Estevez, J.; Graña, M. Artificial Intelligence

• Introduction

Applied to Drone Control: A State of

The advent of advanced autonomous drones and their continuous technological evolution has marked a significant milestone in various industrial sectors improving the performance and capacity of industrial processes. This progress has revolutionized sectors such as agriculture, infrastructure inspection and environmental monitoring. Likewise, innovative applications are emerging, such as the use of drones to create access points, thus providing a constant connectivity service in areas where internet access is limited. Drones have facilitated cargo transportation achieving economies of scale by trajectory optimization and extended autonomies both in range and in operation by the integration of AI in the control systems of drones. The evolution of this technology allows complex decisions to be made autonomously in real time by exploiting Deep Learning (DL) algorithms and massive data processing techniques. The development of autonomous navigation systems provides greater adaptability and efficiency in trajectory optimization, especially in dynamic environments. In addition, AI has proven to be essential in predictive maintenance and failure detection, contributing to the reliability and safety of drones. In the area of cargo transportation, AI has revolutionized logistics operations by facilitating the planning of optimal and adaptable routes. This dynamic approach, supported by real time tracking capability, not only improves operational efficiency but also contributes significantly to building a more sustainable logistics future.

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https://www.mdpi.com/journal/drones

However, the use of AI for autonomous decision making embedded in drones also poses ethical and regulatory challenges. The balance between the autonomy of these systems and human supervision has become a critical point of debate in the development of this emerging technology. Although there are numerous papers that focus on specific aspects of the technology applied in this field, it is of particular interest to make a comprehensive compilation that addresses the various significant applications and algorithms in the field of AI and drones. The existing literature focuses on particular tasks or algorithms, such as cargo transporting [1,2] and transport paradigms [3,4], logistics [5,6], trajectory optimization [7], object detection [8,9], agricultural operations [10,11] and inventory [12,13] without offering a complete view of the global applications of AI drones (Figure 1).

Figure 1. Drone + AI technology.

This study of the state of the art is not limited to cargo transportation developments in the literature, but seeks to identify and examine in detail the most salient AI algorithms that have proven effective in various drone operations. The organization of the contents covers a contextualization of the main AI algorithms and cross cutting theoretical aspects, followed by their applications in drones, taking into account the functional area, innovation, and relevance in this field. A wide range of notable contributions in this field are explored, from the application of DL algorithms for real-time object detection and recognition to the use of massive data processing techniques for dynamic path optimization. The remainder of this paper is as follows. Section 2 is dedicated to explaining the search methodology used in this paper. A background that covers a review of the theoretical foundations of AI and autonomous decision making and other relevant aspects is presented in Section 3. Section 4 describes various avant garde applications, while Section 5 gives a discussion where summarized ideas and aspects are presented from an objective perspective. Finally, the conclusions section provide the key findings and points out future research directions. In order to ease the reading of the paper, a graphical outline is shown in Figure 2.

Figure 2. Review structure.

- Methodology To carry out the study of the state of the art on the selected topic, a structured methodology is followed based on the search and analysis of relevant scientific articles. Queries have been made on Web of Science, IEEE (Xplore Digital Library), and Google Scholar, which have been selected for their extensive content and updated information on scientific articles. During this process, a lot of papers were identified that address the topic of study published in scientific journals and with solid methodological approaches. The detailed review of these articles allows the identification of trends, thus providing a comprehensive view of the current state of AI applications in drones. Due to the large amount of search results, some search and filtering criteria were established. Firstly, some of the main search terms are: “cargo transport* with drones”, “autonomous drone flight”, “cooperative load transportation quadrotors”, “types of UAV cargo”, “delivery of packages with drones”, “delivery of packages with drones”, “cargo transporting strategy UAV”, “cargo transporting strategy multirotor”, “cargo drones”, “drones and logistics” in the title, abstract or keywords of the papers. These terms have been chosen to accurately address the relevant aspects of the research topic and AI. In this case, all terms have been pre-filtered to ensure that everything presented falls within the scope of AI. Some of the main AI-based filtering terms are: “Artificial Intelligence”, “Algorithm”, “Artificial Intelligence Algorithm”, “Machine Learning”, “AI”. As an example, one of the expressions used is: “cargo transportation* with drones * Artificial Intelligence Algorithm”. To facilitate the visualization of the exclusion criteria, a graphical scheme is shown in Figure 3. The primary selection condition was that publication date was after 2019, except when an article published prior to 2019 was deemed exceptionally relevant to the topic (up to 9% of the articles). The main motivation for selecting this date was to establish a lower boundary criterion for a comprehensive analysis of the state of the art from that date onwards. Due to the robustness of the AI algorithms presented and the standardization of many drone operations, it is interesting to set this limit in order to incorporate the most

innovative operations. The purpose here is to showcase applications in this field that are both stable and innovative.

Figure 3. Flowchart of paper selection.

Once all the relevant paper references have been obtained and filtered according to the established criteria, a detailed breakdown is carried out to classify the aspects in which AI affects drone operations. This classification approach has identified specific areas of impact, such as autonomous navigation, visual recognition, drone collaboration, Machine Learning (ML) and ethical and regulatory considerations. In Figure 4, there is a representation of this classification in graphic form, highlighting the most recurrent and relevant topics. This visualization offers a clear perspective of how AI is influencing drone operations, and how these topics interact to drive significant advances.

Figure 4. Distribution of topics.

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- Background Thanks to the development of various techniques and methodologies, AI has experienced significant advances in recent decades. Techniques such as ML stand out for their ability to provide autonomy in decision making through interaction with the environment. ML is an important component of the growing field of data science. Through the use of statistical methods, models are trained to make classifications or predictions by discovering key information in various data mining-based projects. In this context of evolution, DL emerges as an advanced technique within ML, consisting of artificial neural networks with multiple layers. These deep structures allow us to address complex tasks, such as recognizing patterns in images or understanding natural language. There are a wide variety of ML algorithms, and it is beneficial to pre-classify them into categories following some basic criteria. One of the main and most significant criteria is related to the way in which the algorithms are trained. In this classification, four main methodologies are distinguished: supervised learning, unsupervised learning, and Reinforcement Learning (RL). A new type of methodology called semi-supervised learning arises when labeling the data is difficult. Semi-supervised learning is able to handle both labeled and unlabeled data. Most semi-supervised learning algorithms are combinations of unsupervised and supervised algorithms. 3.1. Supervised Learning Supervised learning is defined by the use of labeled data sets to train models that accurately classify data or predict outcomes. This technique allows organizations to solve a wide variety of real world problems at scale, such as sorting spam into a folder other than the inbox. Various algorithms and calculation techniques are used in this process (Support Vector Machine (SVM) [14], K-nearest neighbors (KNN) [15], Random Forest (RF) [16], etc.). One specific branch of supervised learning is DL, which has applications that cover a wide range of fields, including voice and image recognition (Figure 5), automatic translation, medical diagnosis, and autonomous driving.

Figure 5. Feature extraction and object classification using DL.

As a particular case, DL has significantly influenced the evolution of drones, especially in the field of parcel delivery. Drones can now specialize both individually and collectively, adapting to the characteristics of the load, thereby optimizing delivery processes. 3.2. Unsupervised Learning Unsupervised learning carries out the clustering of unlabeled data sets. These algorithms discover hidden data groupings or patterns without the need for any human intervention. Their ability to discover similarities and differences in information makes them the ideal solution for exploratory data analysis, cross selling strategies, customer segmentation, and image recognition. One of the most important algorithms presented in this methodology is the K-Means algorithm [17], whose theoretical basis is based on dividing a set of data into ‘k’ groups or clusters. Its main objective is to minimize the sum of the squared distances between the data points and the centroids of their respective clusters (Figure 6).

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Figure 6. Clustering by the k-means methodology.

As far as the field of drones is concerned, it presents a series of significant benefits and disadvantages. On the one hand, it can be a beneficial strategy in several situations such as object detection, image segmentation,

navigation, and path planning [18]. On the other hand, the k-means algorithm presents some limitations such as the need to specify the number of 'k' clusters a priori, the sensitivity to the initial selection of centroids, and the tendency to produce spherical clusters of similar sizes, implying that in some applications focused on drones, it may be beneficial to explore other types of techniques that obtain more satisfactory results. 3.3. Reinforcement Learning Another of the most important techniques is RL, whose main characteristic is to learn through interaction with the environment, making sequential decisions and receiving feedback, establishing a system of rewards and penalties (Figure 7). The choice of the appropriate strategy is carried out autonomously, trying to obtain the best possible reward in all the decisions that are made. For example, many robots use reinforcement learning to learn to walk.

Figure 7. RL learning cycle.

Like an RL base algorithm, Q-Learning (QL) is presented, whose objective is to train agents with the capacity to make decisions optimally in unknown environments and who present a high degree of dynamism. As it is based on a reward system, it can be applied innovatively in various fields such as collaborative load sharing. In this context, a methodology that takes advantage of RL adopting a hierarchy approach is presented. This approach makes a division into two main strategic levels. The first level or higher level is in charge of making global decisions about the delivery of packages and the second level or lower level is in charge of making decisions about individual drones to meet the objectives. This implementation concept bi-level of the QL algorithm allows establishing greater scalability and improved efficiency at the global level of the system [19]. Performance is demonstrated in terms of efficiency and scalability in the delivery of packages with drones. This methodology not only presents a special advance in logistics with drones, but also stands out for presenting the potential of hierarchical RL to address complex challenges in dynamic environments whose objective is collaborative decision making. Continuing with RL, another fundamental approach in solving sequential decision making and optimization problems is Markov optimization. This methodology is used in situations where the decisions made are only related to the current state of the system, this approach being the fundamental support of the Markov property, which is based on the

fact that the future state of a system is only conditioned by the present state without taking into account the path that led to it. Transferring this methodology to the field of drones, a distributed communication paradigm is presented that enhances collaboration between aircraft in charge of delivery logistics [20]. This mechanism, applied in the context of collaborative delivery, capitalizes on the Markov property by allowing drones to collaborate in real time based only on the systems present state and immediate conditions. 3.4. Meta-Heuristic Algorithms Meta-heuristic techniques are advanced search methods used to address optimization problems that present great complexity. Solving such problems involves the task of identifying the most appropriate solution among an extensive set of possibilities. Although these strategies do not guarantee the identification of the optimal solution in a defined time interval, it has been observed that they can generate high-quality results in time periods considered acceptable. Regarding combinatorial optimization, especially in situations where an individual exhaustive analysis is inefficient, these strategies are predominantly implemented. Paradigmatic examples of meta-heuristic algorithms include the ant colony optimization algorithm (ACO) [21], the genetic algorithm (GA) [22], the simulated annealing algorithm (SA) [23], the tabu search algorithm (TS) [24], and the particle swarm optimization algorithm (PSO) [25]. These tools are used in different contexts, from planning transport routes and managing schedules, to optimizing technical methods and managing telecommunications systems. Meta-heuristic algorithms are valued for their flexibility in addressing complex challenges in which obtaining direct answers is difficult or involves considerable computational cost. To optimize the logistics distribution of goods, a two stage methodology that integrates heuristic and meta-heuristic tactics is recommended. This approach is aimed at perfecting the comprehensive delivery system, combining ground transportation and the use of drones in cities with traffic restrictions [26]. The method comprises two essential phases: the creation of routes for vehicles and drones, which benefit from the use of techniques such as tabu search and the ACO algorithm and the synchronization in the handling of deliveries, where the variable neighborhood search (VNS) is used. Likewise, meta-heuristic algorithms play a crucial role in strengthening communications systems, applying them to the improvement of FANET networks (flying ad hoc networks), seeking optimization through specific procedures derived from said algorithmic tools [27]. As a particular case,

the use of GA in the context of drones has proven to be an effective strategy for addressing various challenges, such as path planning, flight control, obstacle detection, and the optimization of control parameters [18]. These algorithms, inspired by natural evolution and genetics, leverage biological concepts to solve search and optimization problems, especially in conditions where conventional approaches might be inefficient. The basic operation of a GA involves the creation of an initial population of candidate solutions, represented as individuals. The evaluation of these individuals is carried out using a fitness function that measures their effectiveness in solving the problem in question. Through iterations involving selection, crossover and mutation processes, the algorithm generates new solutions, constantly seeking to improve the fitness of the population. This cycle repeats until a stopping criterion is met, such as reaching a maximum number of generations or achieving a good enough solution. The application of GA in the context of drones covers a variety of challenges and problems, from collaborative distribution to route planning and mission assignment in three dimensional environments, highlighting their versatility and effectiveness in solving complex problems in this field.

3.5. Challenges in AI Integration for Drones Due to the large amount of data generated and the computational need to be treated and evaluated, cloud simulation is presented as a novel aspect, an essential tool in the development and research of intelligent systems. Through the ability to simulate complex environments in a stepwise and accessible manner, important advances are enabled in areas such as autonomous robotics, space exploration, and pilot training. Despite the progress made, there are challenges in the integration of AI technology into the operational drones. One of the main challenges is the optimization of DL algorithms for execution in cloud simulation environments. While AI has demonstrated great applications, knowledge gaps persist in areas such as the interpretation of DL models, the adaptability of (RL) algorithms to dynamic environments, and computational efficiency in complex simulations in the cloud. 3.6. Collaborative Communication between Aircrafts Through the implementation of a Deep Reinforcement Learning (DRL) approach, a comprehensive decision-making framework is established, where the drone develops its local policy by directly observing the state of the environment in its proximity and the reception of messages from neighboring drones. This method aims to encourage cooperation between drones in the generation of highly optimized multiple trajectories. This collaborative approach implicitly leads to the minimization of resources needed to carry out operations [7]. The drone, by dynamically learning from its immediate environment, manages to adjust its behavior autonomously. This approach not only optimizes the individual trajectories of the drones, but also contributes to the overall optimization of the system, since the cooperative generation of routes seeks to reduce resource consumption as much as possible. The uniqueness of this approach lies in its ability to adapt in real time to changes in the environment, such as modifications in topology or adjustments in resource availability. Furthermore, by promoting the cooperative generation of optimal trajectories, this distributed RL framework effectively acts in the overall minimization of the resources required to carry out drone logistics operations. The application of this innovative approach not only stands out for its efficiency, but also provides an advanced solution for the collaborative management of drones in dynamic and complex environments. 3.7. AI Wings—Training, Simulation, and Piloting from the Cloud AI Wings represents an innovative drone solution based on the Internet of Things (AIoT) with the purpose of controlling multiple drones and deploying AI models. This system features a highly secure cloud server that serves as a control center to effectively coordinate and direct drone fleets. A distinctive feature of AI Wings is the integration of Virtual Reality (VR) simulation using AirSim drone simulation software. This offers a realistic platform for training and testing, allowing operators to simulate drone missions in virtual environments. This VR simulation facilitates the evaluation and continuous improvement of AI models, thus contributing to the optimal performance of drones in real situations [28]. 3.8. Drone Technologies In this section, some important technical aspects related to drones are presented. Fundamental technical characteristics will be explored, including their payload capacity, flight range and altitude, and battery recharging methods. In addition, the main technical challenges and innovative solutions that are emerging in the field of autonomy and recharging will be discussed. This review will provide an understanding of the technologies that are driving the evolution of drones in various applications. A summary of the most significant references can be found in Table 1.

Table 1. Drone technologies reference table. Reference Number

Year

Features

[29] [30] [31] [32] [33] [34] [35] [36] [37]

2022 2019 2019 2018 2016 2006 2014 2018 2019

Drone classification by morphology Drone classification by morphology Flight time analysis, turning agility and its speed. Common payloads weighing less than 1 kg analysis Low-Altitude Platforms (LAP) Drone classification on altitude Flight time analysis Drone battery charging Strategies to increase flight time

3.8.1. Drone Morphology Drones come in numerous specifications, sizes and configurations. They are classified into four main categories: fixed-wing, hybrid fixed-wing, single-rotor, and multi-rotor, also considering the number of rotors [29,30]. Fixed-wing drones are ideal for aerial surveys and mapping due to their stable and long-endurance flight capability. Hybrid fixed-wing drones combine automation with manual gliding, offering a balance between manoeuvrability and efficiency. Single-rotor drones, while more complex and costly, provide exceptional accuracy for specific tasks, such as detailed topographic surveys. Finally, multi-rotor drones, especially quadcopters, are highly valued for their agility, vertical take-off and landing capabilities, and are commonly used in surveillance and aerial photography applications. Multirotor drones can be tricopters, quadcopters, hexacopters, or octocopters as shown in Table 2. The main characteristics of each of the drone categories can be seen in Table 3. Table 2. Number of propellers for different types of drones. Types of Drones

Number of Propellers

Tricopter Quadcopter Hexacopter Octocopter

3 4 6 8

Table 3. Main features of different drone categories—vertical takeoff or landing (VTOL). Types of drones

Key Features

Fixed-wing Fixed-wing hybrid Single-rotor Multirotor

High speed, long endurance Long endurance, VTOL Long endurance, hovering, VTOL Short endurance, hovering, VTOL

3.8.2. Flight Time Small drones can fly at speeds of less than 15 m/s, while large drones can reach up to 100 m/s. Drone speed must be properly controlled at turning points to improve energy efficiency. In ref. [31], the authors focus on the relationship between the drones turning agility and its speed. Flight time, which is influenced by size, weight and weather conditions, is crucial. Large drones can fly for hours, while small drones are limited to 20–30 min. Other aspects that affect flight time are the autopilot and GPS system. 3.8.3. Payload Capacity and Impact on Drone Performance The payload capacity that a drone can carry varies from a few grams to several hundred kilograms. While a larger payload allows more accessories to be carried, it generally decreases flight time due to the increased battery consumption and size of the drone. Common payloads include sensors and video cameras used for surveillance and

reconnaissance, including electronic devices weighing less than 1 kg [32]. Heavy payloads tend to shorten flight time, but a drone with a larger surface area and more motors can store more energy, which improves flight time. Payload quality can also extend flight duration without sacrificing accuracy and resolution. 3.8.4. Range and Altitude Drones can be remotely controlled from various distances, known as their range, varying from a few metres in small drones to kilometres in larger drones. Altitude, on the other hand, is the height at which they can fly. A classification of aerial platforms is presented based on the altitude they can reach: •

•

High-Altitude Platforms (HAPs): HAPs, like balloons, are also used for mobile connectivity. These High-Altitude Platforms provide more extensive coverage compared to LAPs. However, they are complex to deploy and are

generally used as a means to support internet connectivity. Low-Altitude Platforms (LAPs): LAPs are frequently deployed to support mobile communication due to their fast deployment and low cost. In addition, these platforms provide line of sight (LoS) routing, which significantly improves communication performance [33]. Table 4 presents drone categories based on altitude.

Table 4. Drone classification by altitude [34]. Category

Endurance (h)

Flight alt. (m)

Range (km)

Mass (kg)

0.5–1 >24 24–48 24–48

50–9000 3000 3000 20,000

> 250 >500 >500 >2000

250–2500 15–25 1000–1500 2500–5000

Low-altitude deep-penetration (LADP) Low-altitude long-endurance (LALE) Medium-altitude long-endurance (MALE) High-altitude long-endurance (HALE)

3.8.5. Batteries in Drones Drones are currently used in a variety of applications, such as military operations, power line inspection, disaster prevention, and smart agriculture. These unmanned aerial vehicles carry different payloads, including GPS, infrared cameras, batteries, and sensors. Drones generally use high-energy batteries, such as lithium batteries, which allow a flight time of 20 to 40 min [35]. However, the limited battery capacity poses critical challenges in terms of range and endurance. Increasing the size of the battery is not feasible, as it increases the weight of the drone. Several studies have addressed drone battery charging [36]. Jawad et al. [37] proposed three strategies to increase flight time: equipping drones with higher-capacity batteries, although this increases their weight; swapping batteries after landing, which is complex; and recharging batteries at the drone's base station, using either wired or wireless power transfer systems. 4. State of the Art This section reviews the most promising areas of research where the AI algorithms have made an impact in the development of drone operations. 4.1. Cargo Operations Despite being related to the same application of cargo, there are a number of heterogeneous scopes, which motivates us to divide them into several parts. A summary of the most significant references can be seen in the Table 5.

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Table 5. Cargo operations reference table. Reference number (Ref). Ref

Year

Model

Features

Improvement

[2]

2022

[3]

2019

Benders Decomposition

Optimization routes drone truck

Solutions to the majority of the problem instances

N/A

Distributed load, collaborative routing

Distributed charging system

[5]

2022

Deep Q-Learning

Same-day delivery with vehicles and drones

Improve same-day 10% delivery with drones and stations

[6]

2021

Multi-Model

Last-mile delivery system with multiple transportation modes

[18]

2023

K-Means, GA

Proposed to solve the investigated CVDDN optimization problem

Solve CVDDN

[20]

2021

RL

Drone delivery system

Route planning and task in collaborative

[38]

2022

Analysis article

Critically evaluates the practical reality of integrating UAV deliveries

N/A

[39]

2022

Analysis article

Investigates payload solutions for medium and small package delivery

N/A

[40]

2019

Analysis article

Flexible and automated in-house transportation

N/A

[41]

2021

GA-II (ENSGA-II)

Decomposing the problem into smaller manageable subproblems

Route planning approach for a collaborative drone delivery

[42]

2020

RL

Planning and task allocation in collaborative drone delivery systems

Achieve efficient and effective coordination

[43]

2021

RL

A tasking strategy that considers the workload

Achieve faster and more efficient delivery Simulations validate the method

[44]

2023

AGA

Trajectory planning method using sine–cosine particle swarm

[45]

2023

MIC, GA

Extending Vehicle Routing Problem (VRP)

Algorithms solve the problem efficiently for test instances

[46]

2018

HBERA

Minimizing delivery time and tardiness

Computations show clearly optimal solutions

[47]

2022

FSVRPLW

Drone delivery in which flight time is dependent on the weight

Flight time largely depends on the weight of packages

[48]

2017

N/A

Limitations by integrating quadcopter protective cage

Reduce its storage volume by 92%

[49]

2023

A-Ptr-Net

Trajectory optimization problem

Trajectory optimization

[50]

2020

Distributed Routing Algorithm

A distributed routing paradigm
Effectiveness in time and payload
[51]
2016
Cloud Drones Network
Network of drones with different tasks
N/A
[52]
2018
Prey-predator (HTC and UAV)
Balance MTC and HTC
HTC and UAV can converge to equilibrium
[53]
2022
Red 5G NR
Drone swarm authentication
Quick authentication method
[54]
2021
Routing UAV, KNN, MILP
Reduction in total delivery time, route optimization
Significant reduction in delivery time
[55]
2022
MDPGA
Drone coordination, limited carrying capacity
Reduction in transport costs
[56]
2019
RL
Stability of training
Use of team of three UAVs in training
[57]
2020
PID y PD Control
Transport of suspended loads
Flight model with suspended loads Cost and emission improve
[58]
2023
LNS-QL
Last-mile delivery system with Electric Vehicles (EV)

[59]

2023

LQR

Last-mile delivery

Positive simulation results

[60]

2021

DEA

Comparison of delivery systems

Three systems: only trucks, only drones, hybrid truck–drone

[61]

2023

KNN, Tabu Search

Truck–Drone Delivery Problems (TDDP)

80% of the best known solutions were improved

[62]

2020

PSO

Real-time collision avoidance

Positive simulation, graph-based routing

[63]

2022

Hybrid Metaheuristic

Address traveling salesman problem

Minimize delivery time

[64]

2023

DRL

Long-distance missions

Evaluation through simulations of parcel delivery

[65]

2023

DDPG-LSTM, MDP

Minimization of energy consumption

Evaluation through simulations

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4.1.1. Complexities Associated with Cargo in Drone Transport When addressing the complexities associated with cargo in drone transportation, it is essential to consider both the specific conditions of the products to be transported and the intrinsic characteristics of said cargo. For instance, the need for rapid delivery for perishable products has motivated studies that focus on bi-objective optimization models. These models seek to minimize the costs associated with distribution, also reducing value losses that could occur during the process

[18]. In parallel, the physical characteristics of the cargo, such as its weight, size, fragility, and handling requirements, play a crucial role in selecting the appropriate type of drone. For example, a heavy load may require a drone with a higher lifting capacity, while a fragile load may need an additional suspension system or protection to prevent damage during transport. There are specialized studies that analyze in detail the behavior of different types of cargo during transportation. These sudies take into account variables such as stability, aerodynamic forces and structural resistance, with some studies focusing specifically on loads that do not exceed 5 kg maximum weight [38,39]. These studies also contribute to the design of safe restraint structures and the development of flight strategies that not only minimize the risks associated with cargo transportation, but also ensure the successful and efficient delivery of products. In this sense, detailed understanding of cargo dynamics becomes an integral component to effectively advance the field of drone freight transportation. 4.1.2. Challenges in Cargo Delivery with Drones Despite notable advances in AI that have enabled the development of advanced algorithms for route planning and autonomous decision making by drones, there are additional challenges that require attention, such as efficient battery management and the consideration of external factors such as adverse weather conditions, airspace regulations, weight restrictions and the optimization of recipient waiting time during the implementation of drone delivery systems [40]. Various research focuses on developing solutions that address these specific needs. A route planning approach is proposed for collaborative delivery systems with drones, using GA. This approach considers multiple objectives, such as minimizing route length, delivery time and energy consumption, thus addressing key challenges in drone delivery system efficiency. In the field of collaborative vehicle–drone distribution (CVDDN), an efficient hybrid heuristic algorithm based on improved K-means clustering and extended nondominant sorting GA-II (ENSGA-II) [41] has been proposed. It addresses complex problems such as vehicle–drone collaboration, site selection, and the distribution of perishable products, using clustering strategies for effective localization and routing optimization. Furthermore, another RL based approach for route planning and task allocation in collaborative drone delivery systems is presented [20,42,43]. This method uses RL algorithms and Deep Neural Networks (DNN) to optimize task allocation and drone routes, considering factors such as workload, location, and drone capacity. Performance in terms of efficiency and scalability in drone package delivery is demonstrated using the QL algorithm [66]. In this context, an approach based on GA has been proposed. This approach considers multiple objectives, such as minimizing path length, delivery time and energy consumption, employing an objective decomposition strategy to efficiently address multiobjective optimization [44]. In the field of drone package delivery from a single truck [2], the problem arises of determining the route of the truck and the sequence of trips of the drones to meet customer demands efficiently. This methodology includes an extended graph based formulation and an enhanced Benders decomposition method with relaxations. Additionally, in the field of e-commerce and optimizing package delivery by drones, a mixed integer programming model and a GA based on FIFO and rescheduling are proposed [45]. These algorithms stand out for their efficiency and ability to deal with even large test instances, suggesting their applicability in real-world implementations.

Delivery time and delay in the delivery of packages is a critical problem [46]. Hybrid block-based edge recombination algorithms (HBERA) are presented and shown to be effective when compared with edge recombination crossover algorithms (ERX), especially in handling multi-objective problems. There is a wide diversity of approaches to address the specific challenges in drone package delivery, from route planning to resource optimization and the consideration of multiple objectives. The Markov property thus becomes a fundamental aspect, ensuring that the actions of the drones are aligned with the present state of the delivery environment. The introduction of distributed communication further enhances this principle, allowing agile and adaptive collaboration between drones, demonstrating its effectiveness not only in optimizing package delivery, but also in system efficiency [67]. 4.1.3. Adaptive Models and Transportation Problems Adaptive mathematical models are one of the most promising applications of AI in this field, allowing a better understanding of the cargo transport structure, translating into greater efficiency and profitability. The importance of adaptive mathematical models lies in their ability to enhance logistical planning and optimization by reducing costs and delivery times while taking into account the specific configuration of each transportation method [18]. These models are particularly useful when considering factors such as distance, weight, cargo size, weather conditions or any other relevant variables that may impact the transport process. Recent advancements in AI have also enabled the development of sophisticated adaptive mathematical models,

which can automatically process vast amounts of data and generate optimized algorithms with remarkable efficiency. You can also analyze patterns in real-time and historical data to improve model predictions and accuracy. Another major challenge in drone cargo transportation is the coordination of multiple drones working together to transport a cargo. This technique is known as collaborative drone parcel transportation and is used to transport larger loads that a single drone cannot handle. It is also important to take into account the inertia that a load with a high volumetric can cause, and algorithms must be implemented that are capable of compensating for the mobility of the drone network involved in the operation, counteracting this problem, and avoiding losing both the cargo and the drone network that transports it [47]. To address these challenges, manufacturers are working on the development of more advanced and safer drones by developing ML models that achieve improved coordination and safety. There are several important variables that must be taken into account when which proceeds to the design of some type of AI algorithm based on the calculation of optimal trajectories; these variables are the incidence of wind, weight and volume of the drone, cargo stability, and weather conditions [47]. When drones are included in urban areas or crowded areas, there is a great risk of causing some damage to external agents in the process of the operation. To mitigate this risk, operations are carried out with protective cages implanted in the drones [48]. This type of methodology must be supported by AI algorithms capable of correcting the trajectory and identifying obstacles in real time, since when flying with a protective cage it is much more likely to generate some incident time. 4.1.4. Dynamic Delivery Optimization Based on Demand Fluctuations This system in charge of dynamic delivery optimization based on demand fluctuations uses an advanced neural network architecture to generate organized sequences of delivery locations. Various optimization criteria are taken into account, such as distance traveled, efficiency in the use of vehicles and cost minimization [49]. The particularity of this model lies in its ability to dynamically adjust to changes or updates in real time, such as adjustments to delivery addresses or modifications to orders.

This dynamic capability ensures exceptional flexibility and agile response to situations involving constant fluctuations in demand. This adaptability allows the system to maintain optimal performance even in logistics environments characterized by sudden changes and frequent adjustments. In this way, significant advantages are generated, providing a robust and efficient solution in scenarios where demand is variable and dynamic. 4.1.5. Cost Function Focused on Distance and Waiting Time The cost function-based algorithm is one of the most common approaches to optimize drone package delivery using search algorithms based on a combined cost function. This cost function takes into account both the distance cost, to minimize the total distance traveled by the drones and the waiting cost, to reduce the waiting time for deliveries. Complementing the cost function optimization, a distributed routing algorithm can be proposed, making the drones work collaboratively to deliver the package to the target locations. The algorithm optimizes the assignment of tasks and routes, taking into account the location of the packages and the individual capabilities of the drones [50]. 4.1.6. Organizational Management of Several Drones One of the main challenges is to programme and manage multiple drones to optimize the efficiency of cargo deliveries. When working with a fleet of drones, it is essential to coordinate and synchronize their operations. This involves designing intelligent algorithms and scheduling systems that assign the appropriate tasks to each drone, taking into account factors such as payload capacity, flight range, and availability. Additionally, managing multiple drones involves monitoring and controlling their performance in real time [51]. It is necessary to monitor the location of each drone, the state of charge of its battery, its health and any anomalies that may arise during the flight. To do this, telemetry systems and sensors can be used on drones, which send information in real time to a control center and guarantee stability in connectivity [52]. This allows quick and effective decisions to be made to ensure delivery success. It is also necessary to have an effective and latency free authentication system to be able to identify all the drones that participate in that operation [53,68,69] and to be able to keep them located as best as possible within predefined location methodologies to avoid all types of conflicts during maneuvers in the that airspace can be shared [70,71]. 4.1.7. Collaborative Routing and Distributed Cargo A significant development in the logistics field is the adoption of a collaborative approach in the route design and equitable distribution of cargo. These components are essential to maximize efficiency in delivery processes. This collaborative routing and distributed cargo approach involves the use of multiple drones operating in a coordinated manner to deliver cargo efficiently and quickly. Collaboration between drones allows delivery routes to be optimized, reducing times and maximizing the efficiency of the system as a whole [54,55,72]. To complement this strategy,

distributed charging systems are implemented. These systems ensure that drones have enough power to complete their missions, through charging stations strategically located along delivery routes. In this way, the drones can charge their batteries, maintaining their autonomy throughout the delivery process. Research into this transportation paradigm focuses on route planning and optimization algorithms, taking into account variables such as distance, air traffic, the location of delivery destinations, and the characteristics of the transported cargo. These types of decisions can be made using DL with graphs, which can assist in real-time decision making [73,74]. Additionally, charging planning algorithms are used to determine the optimal location of charging stations along routes [3]. The effectiveness of this methodology is evaluated through extensive simulations, comparing the results with existing approaches. Collaborative routing and distributed

charging are observed to achieve faster and more efficient deliveries compared to more traditional approaches. The study and design of this type of methodology must take into account some fundamental aspects such as route planning, coordination between drones and shared load management. These coordination principles play a fundamental role in ensuring that drones operate harmoniously and efficiently, avoiding collisions and optimizing payload distribution [75]. Another approach used is the leader/tracker paradigm, where one drone acts as a leader and the others as trackers. This paradigm has been combined in some studies with cooperative transport with a load suspended by cables [4,56,76–78]. The importance of considering possible delays in decision making due to the network is highlighted. Some studies anticipate this phenomenon and analyze how it would affect the behavior of the drone network in such circumstances [57,79]. Simulations in virtual environments are essential to evaluate collaborative routing and distributed cargo without risking the integrity of the drones or the environment. Compared to traditional delivery approaches, it has been shown to significantly improve transportation efficiency, reducing delivery times, optimizing the use of resources, and minimizing the number of trips made. 4.1.8. Last Mile Delivery Optimizing the generation of itineraries in the parcel delivery paradigm with several drones transported by a truck poses challenges that require advanced approaches to achieve the efficient distribution of packages [5,6,58]. This approach is characterized by the use of a long-range means of transportation, such as a truck, which acts as a central base for collecting packages and an approach point to delivery areas. Meanwhile, drones are responsible for making deliveries to specific locations nearby. A recent study addresses the optimization of a last mile delivery system that combines vans and drones [6]. The research highlights the combination of three transportation methods: vans, drones, and trucks. The drones and vans are responsible for distribution services, while the trucks are responsible for transporting the merchandise and the drones to the stations. A discrete optimization model and a two-phase heuristic algorithm are presented to optimize the total delivery cost, including the transportation costs of the vans and the delivery cost of the drone. The results indicate significant cost savings by combining traditional delivery modes with the use of drones and drone stations. Another of the most promising studies in this field presents an innovative hybrid delivery methodology, leveraging the combined use of drones and trucks. This approach focuses on optimally guiding drone missions through a receding horizon linear quadratic regulator (LQR), effectively managing takeoff, free flight, pickup, delivery, and dynamic landing on a moving vehicle. Simulation results of the truck–drone delivery architecture are presented and discussed in detail, proving the effectiveness of the proposed method [59,60]. Other research addresses same-day delivery with vehicles and drones [5]. A Deep Q-Learning (DQN) approach is proposed to assign clients to vehicles or drones dynamically. The method learns the value of assigning a new client to vehicles or drones and demonstrates its superiority compared to baseline policies. This approach uses different vehicle fleets based on capacity and speed, leveraging their strengths to optimize same day delivery. On the other hand, a last-mile delivery system with electric vehicles (EV) and drones is being studied, where battery-swapping vehicles (BSV) offer a mobile battery exchange service for EVs. A mixed-integer programming model (PIM) is formulated and a large neighborhood search algorithm based on QL (LNS-QL) is designed [58]. This approach seeks to minimize the total cost considering energy consumption, driver salaries, and obsolescence costs. The results of the experiments verify the effectiveness of the model in small-, medium-, and large-scale instances, demonstrating the viability of the cooperative delivery system of EV and drones.

These studies reflect the diversity of approaches to address the challenges in generating itineraries for package delivery with drones and other vehicles applied to the last-mile delivery paradigm, highlighting the importance of considering diverse fleets, energy efficiency, and DL to optimize package distribution. 4.1.9. Delivery in Urban and Catastrophic Areas Delivery of cargos in urban areas assisted by drones provides speed, agility, traffic decongestion, and greater flexibility due to the ability to access difficult or traffic restricted areas; as a consequence, packages can reach destinations that would otherwise be complicated for traditional delivery services. In order to achieve an effective and controlled delivery with drones within urban areas, various methodologies supported by AI algorithms are proposed. One of the most widespread paradigms consists of transporting a fleet of drones by trucks to the urban areas of cities. From this point, the aircraft are launched with the respective packages for delivery [1,6]. Once the delivery is complete, each drone will return to the truck to pick up the next package [2,61]. In order to optimize parcel collection and distribution points on roads, the development of AI algorithms is proposed with the charge of choosing these optimal points [62,63]. With the aim of streamlining the order/delivery system, approaches are proposed where, when placing an order, the optimal route is immediately planned and the task is assigned to one of the available drones. Not all orders can be managed using this method, as there are operational limitations on the part of drones. Therefore, it is necessary to implement a system that identifies the viability of delivering through this route. To address this challenge, numerous studies use algorithms such as QL, K-means or GA to carry out the feasibility analysis [5,80], achieving the most efficient distribution possible [18,81]. Due to the nature of operations delivery in urban zones, the drones used must be able to modify their structure. Thanks to this morphological flexibility, they are able to adapt to various types of cargo and the environment [40]. As a novelty, the creation of an auction model is presented in which available deliveries are published and the drones postulate these depending on the characteristics of the distribution [82]. Some studies, due to their combinatorial complexity, are only proposed at a theoretical level [82]. Also, an analysis of transportation networks must be carried out, due to the high demand for the use of drones for this type of operations, and algorithms can be applied to predict demand in specific geographic areas in order to carry out delivery planning much more efficient [83–85]. In catastrophic areas and emergency situations, quick and efficient access to medical supplies and services can mean the difference between life and death. In this context, drones have emerged as a highly important tool for the delivery of life support in disasteraffected areas. These aircraft not only provide medical aid and essential supplies, but can also carry out search and rescue tasks, making it easier to locate trapped or endangered people. Another of the most significant features is the ability to transmit information in real time to emergency teams, providing an aerial view of the situation and helping in strategic decision making. The combination of drones with AI can further enhance the efficiency and effectiveness in this type of operations. Planning optimal trajectories is one of the main applications of AI algorithms in this type of circumstances, maximizing the speed and safety of life-support deliveries, avoiding obstacles (one of the most used techniques for obstacle avoidance is RL) [43,86–88], and guaranteeing the delivery of supplies efficiently and fairly [18,84]. The identification and recognition of individuals, real time analysis of medical data, and logistics and resource management in environments affected by limitations are other complementary examples in which the technological fusion between drones and AI algorithms is present. In addition, simulations are presented in environments with diverse characteristics with the purpose of understanding the behavior of drones in different cases, being able to determine the optimal conditions for operation.

Furthermore, in three-dimensional rescue mission environments, a mission assignment method based on adaptive GA and trajectory planning with sine–cosine particle swarm optimization (SCPSO) has been proposed [45]. This method addresses challenges such as 3D terrain modeling, common threats, and drone performance considerations. In the domain of secure communication networks, Markov optimization emerges as a crucial technique. Outside the logistics domain, this methodology is presented as a tool to address the challenges of communication security in Internet-assisted drone networks in urban environments [64], reducing communication issues during emergency situations, such as earthquakes or landslides [65]. 4.2. Agricultural Operations The union of AI with drones has completely transformed the way we grow and harvest food, taking agriculture to new points of efficiency and sustainability. Drones have revolutionized agriculture, offering farmers an aerial view of their land. This perspective has allowed the detailed monitoring of fields, making the early detection of problems and data-based decision making easier [89]. The ability of drones to cover large

areas of land with speed and precision has changed the dynamics of modern agriculture. Convolutional neural networks (CNN) equipped on drones have proven effective in the early identification of plant diseases [90,91]. By analyzing detailed images, these networks can discern specific patterns, allowing farmers to take preventive measures before the problem spreads, thereby improving the overall health of crops. By combining RL algorithms and neural networks, the most effective routes for precise spraying can be determined [92,93]. This combination of constant monitoring and optimized spraying improves both the quality and quantity of crops. Pollination is vital for food production, and drones have taken on a crucial role even in this process. Using AI systems, they can classify images to identify unpollinated flowers and, if necessary, carry out artificial pollination [10]. This capacity guarantees the reproduction of plants and crops, contributing significantly to global food security. On the other hand, the detection of flooding and weeds has been observed and controlled [11]. Using algorithms such as eXtreme Gradient Boosting (XGB) [94,95], SVM [14,96], RF [16,97] and KNN [15,98], drones can identify flood-prone areas and precisely eradicate weeds [99,100], ensuring resilient and healthy agricultural production. These algorithms continually learn and adapt to changing soil conditions and crop needs, ensuring constant improvement in the operations for which they have been designed. A summary of the most significant references can be found in Table 6. Table 6. Agricultural operations reference table. Reference number (Ref). Ref

Year

Model

Features

Improvement

[10]

2023

ML

Using small drones to forage and pollinate flowers

[11] [14] [15] [16] [89] [90] [91] [90] [91] [96] [97] [98]

2023 2021 2016 2020 2021 2023 2023 2023 2023 2021 2023 2023

Detection of flooding and weeds Detection flooding and weeds Detection flooding and weeds Detection flooding and weeds To highlight the importance of drones in agriculture To review the actual progress in crop disease detection Automation of plant disease detection Analysis of drone technologies in the agricultural sector Optimize pesticide spraying Detection flooding and weeds Detection flooding and weeds Detection flooding and weeds

[99]

2023

ML SVM KNN RF N/A ML CNN ML, DL RL, DNN SVM RF KNN Analysis of publications

Identify and pollinate areas in need (87.3% accuracy) Detecting flood zones Detect flood zones Detect flood zones Detect flood zones N/A N/A % of disease detection N/A RL is more effective Detect flood zones Detect flood zones Detect flood zones

Detection flooding and weeds

Detect flood zones

[100]

2023

RF, XGB, KNN, SVM

Detection flooding and weeds

97% (RF, XGB)–96%, 72% (KNN, SVM)–97%, 97% y 80% (RF, KNN y SVM)

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4.3. Drone Identification and Detection The proliferation of drones has generated great expectations due to their ability to be applied in various areas, but on the contrary, it generates concern regarding their misuse and the potential threat they pose [101] due to their invasive nature. There is a proliferation of studies in the field of detection and monitoring, carrying out comparisons between methods based on Linear Kalman Filters (LKF) and Non-Linear Polynomial Regression (NPR) [101]. In addition, techniques based on AI are explored for detection and recognition [101]. One of the most innovative aspects regarding drone detection involves the use of skinny patterns and iterative neighborhood component analysis (INCA) [102]. This classification model uses techniques such as decision tree (DT), discriminant (D), SVM, KNN and ensemble classifiers (EC), achieving a classification accuracy of 99.72% [102]. In another context, a game theory based on the Apolonio circle and QL for cooperative drone hunting (ACGQ-CH) is proposed [103]. This method uses strategies based on the tracker/evader paradigm, guiding trackers to achieve effective cooperative hunting [103]. The ability to identify and detect drones in real time is crucial to maintaining security, which is why drone detection and tracking systems are designed in real time, combining multiple DL [104,105] and computer vision techniques [106]. These systems use the Yolo-v4 model to detect drones and generate visual models for their tracking [106]. On the other hand, end-to-end models are developed for the detection and classification of different drones using YOLOv2 as an object detection model [107]. The use of multiscale time frequency convolutional neural networks for the detection and identification of drones based on radio frequency signals [108] is presented as one of the most novel and promising approaches, surpassing existing methods in the detection and identification of drones by radio frequency using DNN [108]. Additionally, the use of DRL is explored to counter drones in a 3D space using another drone [109]. This method uses the DQN algorithm combining imitation learning and RL to hunt down target drones [109]. Due to the malicious use of drones, physical security and privacy are also of concern. The autonomous detection and identification of drones have become essential to address this type of problem. The use of the acoustic characteristics of drones and advanced deep learning techniques is presented as one of the most innovative and promising techniques to solve this problem [110]. The introduction an acoustic dataset hybrids of drones, which includes audio recordings from real drones and artificially generated audio samples, has been instrumental in improving the detection and identification of this type of aircraft [110]. Additionally, applying Generative Adversarial Networks (GANs) to generate drone audio snippets has proven beneficial in detecting new and unknown drones, thereby improving physical infrastructure security and privacy [110]. A summary of the most significant references can be found in Table 7. Table 7. Drone identification and detection reference table. Reference number (Ref). Ref

Year

Model

Features

% Accuracy

[101]

2023

Kalman Filters (KF)

Drone (UAV) detection and tracking

N/A

[102]

2023

DT, Discriminant (D), SVM, KNN and EC

ADr detection on skinny model and INCA patterns

99.72% using KNN

[103]

2023

Apollonius Circle and QL For Cooperative Hunting (ACGQ-CH)

The hunting time by 16.83, 27.35 and 12.56%

N/A

[104]

2021

DL

Intruder drone target detection

N/A

[105]

2017

DL

Drone identification through imagery

11–16% improvements

[108]

2023

DL, DNN

Radio frequency detect and identify drones

99.7%, 84.5%, 46.8% detection (presence, type, flight)

[109]

2022

DRL, DQN

Counter a drone in 3D space using another drone

Successful hunt for the invading drone

[110]

2021

DL

Detect and identify processes using acoustic

N/A

4.4. Detection, Analysis and Inventory In ecology, the complexity of subtropical mountain forests has challenged scientists for years. Thanks to high-resolution detection images captured by drones, the diversity of tree species and their status can be accurately mapped. This approach has achieved an accuracy of 83% using four object based classification algorithms (KNN, Classification and Regression Tree (CART), SVM, and RF) [111]. In marine environments, seagrasses play a vital role in coastal conservation. Using high-resolution imagery from unmanned aerial systems, several ML algorithms have been evaluated for object-based classification of submerged seagrasses. The Bayes classifier excelled with 94% accuracy under favorable environmental conditions [112]. Exploring the application of drones in forest fire detection, the combination of DL object recognition with drones equipped with specific sensors is investigated. Their analysis highlights the effectiveness of fully equipped drones for real time monitoring and early fire detection, using models such as YOLO and R-CNN [113]. DL approaches to wildfire classification, detection, and segmentation outperform traditional methods and provides a detailed analysis of the data sets and challenges present in current research [114]. In the field of road safety, a computer vision-based method is proposed to detect pavement markings in school zones using high resolution aerial imagery. Their method, based on techniques such as DL or ML with an accuracy of 94%, highlights how drone technology can improve the collection of critical data for road planning and safety [115]. RL algorithms have significantly improved trajectory planning, ensuring the

flight safety of drones in complex tasks, such as detecting aquaculture cages scattered at sea. Thanks to this trajectory planning methodology, drones can save energy while completing complex tasks and return to the ground base safely [87]. In the field of aerial surveillance, the optimization of quadcopter performance is explored through the integration of helium gas. Likewise, drones are used for object detection by using the Tensor Flow object detection API. This strategy not only provides advanced solutions for drone based surveillance, but also strategically highlights the impact of helium on critical factors such as flight time, battery consumption, and maneuverability [116]. Methods are presented for the automatic monitoring of garbage on beaches through the use of drones and object detection based on YOLOv5, demonstrates the feasibility of automation in the identification and geolocation of trash objects in drone images, providing key elements for an automated surveillance and recovery system [117]. Focusing on inspection using AI and unmanned aerial vehicles (UAV), an innovative object detection system is presented that uses RGB images from drones to detect and georeference traffic signs, improving inventories in civil infrastructures. The methodology includes the creation of a data set, model training (Faster R-CNN) and testing. Despite challenges such as the lack of labeled data, the computer vision component achieves accurate traffic sign detection [12]. This type of identification and counting methodology is also used for inventories of spruce seedlings [13]. As a complementary study, the integration of drones in railway diagnostics is presented as a significant advance towards the automation and optimization of track inspection, demonstrating a notable improvement in the speed and efficiency of operations [118]. In the field of infrastructure inspection and maintenance, automated optical inspection of the Fast Aperture Spherical Telescope (FAST) has become more efficient thanks to drone technology and DL techniques. This application guarantees the stable operation of the FAST, providing a reliable and effective solution for maintenance tasks [119]. On the other hand, the Keras-RetinaNet model with ResNet 50 is used for object detection, achieving an accuracy of 77.99%. This innovative approach highlights the potential of neural networks in improving object detection in aerial environments [8]. Additionally, civil infrastructure assessment has been improved through DL deployed on drones. These innovative systems have been applied in the automated evaluation of cracks in high-rise bridge pillars, improving the safety of civil structures. This combination

of technologies has allowed a detailed and accurate evaluation, ensuring the integrity of critical infrastructures [9]. In recent years, the use of drones and robotics has expanded into many commercial uses, including the construction industry. Drone powered automation has a huge impact on improving productivity, reducing costs and schedule delays. The use of drones, along with the application of the IoT and robotics, can have a significant impact on the supply chain and improve inventory accuracy, leading to faster and more profitable construction projects. Optimization models are proposed for supply chain management through the accelerated use of drones and AI in the post-pandemic era. Cutting-edge drone technology can perform rapid inspections to make inventory control more economical and efficient. While certainly not suitable for every building surveillance task, drones have many advantages for investigating buildings for leaks, conducting aerial surveys and addressing security issues more cost-effectively than manual procedures, leading to an improvement in communication and collaboration between different stakeholders [120]. As an innovative system in the field of object detection, a real-time system based on the DL model known as YOLO (you only look once) is implemented. This detector allows the relative position of each drone in the platoon to be continuously estimated. Each drone is controlled using a PD proportional derivative (PD) feedback system specifically designed for platooning [121]. A summary of the most significant references can be found in Table 8. Table 8. Detection, analysis and inventory reference table. Reference number (Ref); detection analysis (DA); inventory (I). Ref

Year

Model

Features

% Accuracy

DA

I

[8]
2023
Keras-RetinaNet with ResNet 50
Detected buildings
Average 77.99%
Yes
N/A
[9]
2021
DL
Evaluation of cracks in high rise bridge pillars
N/A
Yes
N/A
[12]
2023
DL
Detect and geo-reference different traffic signs
55% reduction in time; 55% increase in safety
Yes
Yes
[13]
2023
CNN
Aerial inventories of spruce seedlings
84% mean accuracy, 97.86% detection
Yes
Yes
[111]
2023
KNN, CART, SVM y RF
Tree condition identification
83% with KNN
Yes
N/A
[112]
2023
Bayes DT RT KNN SVM
Classifying seagrass meadows
94% Bayes classifier–18–97% SVM
Yes

N/A

[114]

2023

DL

Remote fire detection systems

90% average in the various cases

Yes

N/A

94%

Yes

Yes

[115]

2023

DL, Computer Vision

Detect school zone pavement markings

[87]

2023

MDP, QL, DQL

Detection of aquaculture cages scattered at sea, obstacle avoidance

50% improved computational performance

Yes

Yes

[117]

2023

DL, YOLOv5

Object detection, detect litter objects in footage

50–95%

Yes

Yes

4.5. Flight Control and Safety Fundamental aspects of UAV flight research are visual navigation, flight control, safety, and route planning. In terms of visual navigation, optical flow algorithms are used in combination with supervised learning techniques (KNN, SVM) to calculate flight speed and improve identification of its motion state [122]. In addition, RL methods are explored that combine the artificial potential field algorithm with DQN to avoid obstacles during flight, allowing safer and more efficient navigation of drones [123]. In the aspect of security, countermeasure systems have been developed using RL for Combat Unmanned Aerial Systems (C-UAS) [124]. These systems employ spoofing and beaconing algorithms to neutralize GNSS receivers of invading drones, guiding them toward safe kill zones (SZ). This technique has proven to be effective in identifying and reducing unauthorized drone flights, thereby improving safety in various scenarios.

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Intrusion detection algorithms based on QL (Q-TCID) are proposed to improve the accuracy in the detection of malicious attacks on Internet of Drones (IoD) systems [125]. This methodology employs an intelligent dynamic voting algorithm and QL optimization strategies to significantly reduce the probability of false positives and

negatives in intrusion detection, thereby improving security in environments where drone and IoT integration is crucial. Route planning and obstacle avoidance are also areas of intense research. Some works have used RL based on the QL algorithm to improve the efficiency of trajectory planning, especially in complex environments such as three-dimensional ocean space [87]. These approaches have allowed drones to perform optimal trajectories and avoid collisions more effectively, even in the presence of unforeseen obstacles. Trajectory planning and flight control research is carried out with the purpose of improving network performance in Drone Base Station applications. It is observed that solutions obtained by QL and DQN achieve an optimized trajectory and consequently, an improvement in the performance of the network, adapting its positioning and mobility according to the movements of the users [126]. For maritime reconnaissance, adaptive route planning for maritime drones has been a constant challenge. Conventional path planning methods have focused on the mesh routing environment, which is often unsatisfactory in a continuous maritime space. To address this problem, an innovative QL enhanced method for maritime drone trajectory planning on the ocean surface is presented [127]. The proposed approach discretizes the flight environment of maritime drones into a state space represented by several variables, which significantly helps in reducing the complexity of the problem. During the training process, a state aware guided learning strategy is implemented to accelerate the convergence of the algorithm. In addition, DRL methods have been developed to perform autonomous front view shooting [128] in the cinematographic field, allowing drones to capture complex dynamic scenes without human intervention. By employing a combination of RL and a PID controller, dynamic and robust control is achieved. The training process involves applying the QL algorithm in a simulated environment, followed by real-world testing to validate the effectiveness of the model. As a practical application, a drone is presented navigating through a three dimensional environment full of obstacles, demonstrating the versatility of this novel control methodology in real world situations [129]. In the context of the integration of drones with the IoT, solutions are proposed that combine DRL and graph search methods for three-dimensional path planning in complex environments [130]. These approaches have enabled drones to make autonomous decisions with the same flexibility as human operators, thus improving efficiency and adaptability in various industrial applications. A summary of the most significant references can be found in Table 9. Table 9. Flight control and safety reference table. Reference number (Ref); detection capabilities (DC); security (S); Internet of Drones (IoD); safety enhancement (SE). Ref

Year

Model

Features

DC

S

% Security

IoD

SE

[122]

2023

Optical flow control algorithm, KNN, SVM

Flight speed, vertical takeoff and landing

Yes

N/A

N/A

N/A

N/A

[123]

2023

DQN

Regular UAV behavior, urban air traffic control

N/A

Yes

N/A

N/A

N/A

[124]

2023

RL, spoofing, meaconing

Security control, counter unmanned aerial system (C-UAS)

Yes

Yes

99% within 75 m radius

N/A

N/A

[125]

2023

Q-Learning, Q-TCID, Markov optimization

Intrusion detection, IoD

N/A

Yes

N/A

Yes

N/A

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Table 9. Cont. Ref

Year

Model

Features

DC

S

% Security

IoD

SE

[128]

2018

RL

Autonomous flight

Yes

[129]

2020

RL, QL

Obstacle avoidance

Yes

Yes

N/A

N/A

Yes

Yes

N/A

N/A

Yes

[130]

2024

DQN

Obstacle avoidance, path planning

Yes

Yes

6% computation time

N/A

N/A

4.6. Hotspots Habilitation The realization of communication hotspots with drones has emerged as an innovative solution to improve connectivity and provide services to mobile users. By employing drone-mounted base stations, we seek to overcome ground infrastructure challenges and maximize mobility to deliver efficient and improved connections in specific areas. In a scenario where drone-mounted base stations freely navigate over a macrohotspot to serve mobile users on the ground, a mobility control algorithm is proposed that significantly improves packet throughput [131]. The constant movement of drones reduces the distance between base stations and users, improving the probability of line-of-sight connection. Simulations demonstrate an 82% increase in average packet throughput and a striking 430% increase in 5th percentile packet throughput compared to a reference scenario where drones hover over fixed locations. UAV-mounted base stations (UAV-BS) [132], also known as drone base stations, have the potential to overcome the limitations of ground-based base stations. These stations can provide cost-effective Internet connectivity to users outside the infrastructure and act quickly in the event of unexpected ground station failures. To optimize UAV-BS mobility and maximize network performance, an advanced DRL-based solution with a continuous actor–critic approach, supported by AI technologies, is proposed. Simulation results reveal significant improvements compared to QL, DQN, and conventional algorithms, achieving a total data rate of up to 45 Mbps and reducing convergence time by 85% compared to traditional methods, clearly demonstrating the effectiveness and efficiency of the proposed DRL-based solution and the application of AI techniques. The adaptability and continuous learning capability of the DRL and AI-based solution opens new perspectives for the evolution of autonomous and advanced systems in the field of mobility and connectivity. A summary of the most significant references can be found in Table 10. Table 10. Hotspots habilitation reference table. Reference number (Ref); connection speed (CS); drones in constant movement (DCM); hotspot generation (HG); base stations (BS). Ref

Year

Features

Network Performance Improvement

CS

DCM

HG

BS

[131]

2018

Movement control algorithm

82%

N/A

Yes

Yes

Yes

[132]

2023 Continuous critical actor RL/ACQL

85% compared to other lines based on QL and DQL

45 Mbps

Yes

Yes

Yes

4.7. Sustainability and Energy Management One of the main problems that present a challenge today is energy efficiency management. Energy is essential for all operations carried out by a drone, from takeoff to flight and landing. This energy efficiency depends on several factors, such as battery capacity, motor efficiency, or the overall design of the aircraft. More and more manufacturers are focusing on the design of aircraft capable of much more efficient energy management [133]. To achieve this goal, AI algorithms are used to manage energy in drones. These algorithms must be adaptive and must have the capacity to make decisions in real time, since the aspects that influence the energy consumption of drones are not only due to internal factors but also due to external factors such as inclement weather.

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These models can optimize the use of energy throughout the flight process. One of the most significant uses is the use of algorithms in charge of planning the most efficient routes whose objective is to minimize energy consumption by avoiding longer routes or with a number of obstacles that make the operation unfeasible. On the other hand, these algorithms must also be able to modify parameters such as flight speed and altitude that can have a negative impact in terms of energy efficiency. One of the critical aspects in the energy management of drones is the payload. This must be managed appropriately to be able to carry out efficient energy optimization [88]. It is very important to implement AI algorithms focused on maximizing energy efficiency through energy management. payload. They must also contribute to the weight distribution design to minimize the resistance that the environment provides to the aircraft. Not only does energy efficiency have to be studied at the time the aircraft is in flight, it is also very important to observe in takeoff or landing, since they are the critical points during which the most energy is consumed. Therefore, AI algorithms whose purpose is to achieve maximum efficiency in takeoff and landing have been designed [134]. A summary of the most significant references can be found in Table 11. Table 11. Sustainability and energy management reference table. Reference number (Ref); year (Y); features (F); number of tests (NT); package weight (PW); emissions (E); emission reductions (ER); maximum range (MR); network of urban warehouses (NUW); passing stations (PS); gas reduction (GR); reduction of energy consumption (REC). Ref

Y

F

NT

PW

E

ER

MR

NUW

PS

GR

REC

[133] [134]

2018 2022

N/A N/A

N/A 128 flights

N/A 0.5 kg

N/A 70 g CO2

N/A 94% lower

4 km N/A

Yes N/A

Yes N/A

Yes Yes

Yes Yes

- Discussion The synergy between AI and drones is emerging as a dynamic and promising field of innovation. Drones that were originally designed for unmanned aerial operations, have undergone a significant transformation thanks to the integration of AI algorithms. The growing availability of onboard computing power and the constant improvement of AI algorithms allows the design of tasks capable of adapting to changing environments, enabling drones to make complex decisions in real time. Security, both in visual navigation and environmental control, emerges as a significant application. The ability to avoid obstacles and to perform terrain recognition in real time has become a priority, together with the consideration of software attacks that may compromise safe drone operations. The identification of drones, especially those that are not catalogued, is acknowledged as a critical challenge. Although systems based on sound waves and radio frequency have proven effective with known drone models, uncertainty arises when it comes to new models. Overcoming identification issues requires AI developments that allow systems to learn quickly and accurately as they encounter new signals and drone models. Another fundamental aspect of security is cargo management, with concerns ranging from onboard resource limitations to personal and material security. This challenge, although largely negative, highlights the need for continued innovation in drone design and payload management, because, in this application, drones are the main limiting factor. Due to drone resource limitation (i.e., battery, payload capacity, energy consumption, weather adversities, data storage limit, connectivity, and response time), AI algorithms promise the ability to analyze and process data in real time, allowing drones to make informed decisions about how best to use their limited resources. For example, ML algorithms can predict energy consumption patterns and optimize flight paths to maximize range. Furthermore, the ability of AI to adapt to changes in environmental conditions or assigned tasks contributes to a more effective optimization of available resources, maximizing the usefulness of these aircraft in various applications.

Innovative and promising collaborative delivery and distribution paradigms face technical challenges like fleet coordination, obstacle avoidance in circumstances in which the cargo is transported by several drones, integration with urban infrastructure, integration with air and ground regulation standards, and connective security due to an interconnection is required between the aircraft that affect the operation. Also, last-mile delivery establishes itself as a key strategy in logistics operations, allowing products to be brought directly to the final destination. This approach is not without challenges that must be addressed in order to guarantee the efficiency and effectiveness of this type of operations such as urban congestion, high operational costs, energy efficiency, package security, fleet location and integration systems, environmental impact, limitations in the autonomy of drones, restricting regulations, etc. Drone operations have significantly impacted agriculture, taking advantage of the versatility of these aircraft and the power of AI algorithms for visual recognition. This combination has improved the quality of crops by allowing the identification of affected areas, whether due to infestations, low fertility, risk of fire, or need for fumigation. In addition, drones themselves can carry out fumigation tasks, highlighting their ability to perform specific operations efficiently in agricultural environments. The AI technological paradigm addresses a multitude of uses, all seeming to be relevant, interesting and beneficial. Regarding sustainability and energy efficiency, there is a need to create more efficient and lighter batteries, as well as the exploration of alternative energy sources, achieving a lower environmental impact. To address these challenges effectively, it is essential to harness the potential of AI algorithms. On the other hand, in terms of regulatory activity, there is an ethical and legal gap in the massive collection of data, very relevant for AI paradigms. Preserving privacy and the risks of autonomous decision making raise questions about the responsibility and regulation of operations, requiring clarifying and robust standards that guarantee trust and coexistence of the various drone platforms and their operations. In this context, the introduction of AI presents itself as a potential solution to address some of these challenges. The ability of AI to optimize fleet coordination, improve energy efficiency, and ensure safe operations could make the difference in the successful implementation of this paradigm. Even though it is a novel paradigm that offers many benefits, it must also be implemented with caution, since it can cause unexpected problems. DL has emerged as a key enabling technology for drone-based functional uses (Figure 8).

Figure 8. Drone operations based on DL.

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- Conclusions The integration of AI technologies with UAV systems enables the creation of advanced and efficient solutions for a wide range of technical applications. The background review in this paper provides a contextualization of the theoretical foundations and main classifications of IA, allowing a deeper understanding of how the technology has reached its current state. This analysis has not only provided an in-depth overview of the algorithms, but also highlights innovative applications, thus offering a comprehensive view of the technological cutting edge in this dynamic field. Among the novel applications identified, advanced solutions stand out for the optimization of trajectories, detection and recognition of objects in real time, assistance in agricultural operations (crop monitoring, pesticide application, and efficient resource management), as well as the development of autonomous navigation systems. In the field of transportation, the emerging application of drones in collaborative transportation stands out, allowing the efficient delivery of products and services. This collaborative approach extends to last-mile delivery, where drones play a crucial role in the logistics chain, shortening distances and optimizing the delivery of goods to final destinations. Furthermore, these pioneering applications not only enrich our current understanding of the capabilities of AI in drones, but also outline essential directions for future research. This technological evolution reflects the growing diversity of uses that these devices can have in different sectors, promoting efficiency and transforming the way we approach various operations. The future outlook for this technology is highly promising, although it faces some significant obstacles. The design of efficient and sustainable batteries stands as a fundamental challenge, since it constitutes a pillar for the advancement of operations related to AI algorithms and drones. On the other hand, but no less important, ethical, regulatory, and privacy aspects are crucial to help establish defined standards in this technical field. If these essential aspects can be successfully addressed, the future of this technology looks extremely interesting, both in the logistics field and in the transformation of employment. Resolving the challenges

raised will not only open new possibilities in terms of efficiency and applications, but will also contribute to forging a solid framework. Consequently, an exciting and transformative future is foreseen for the integration of AI and drones in both society and industry. Author Contributions: All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by D.C.-M., J.M.L.-G., J.E. and M.G. The first draft of the manuscript was written by D.C.-M., and all authors commented on previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript. Funding: The authors were supported by the Vitoria-Gasteiz Mobility Lab Foundation, a governmental organization of the Provincial Council of Araba and the local council of Vitoria-Gasteiz under the following project grant: "Generación de mapas mediante drones e Inteligencia Computacional" and "Generación de Inventario Automatizado de Señalética mediante Drones e Inteligencia Computacional. Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors. Conflicts of Interest: The authors declare no conflict of interest.

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Drones in Insect Pest Management K. S. Subramanian 1*, S. Pazhanivelan 2 , G. Srinivasan 3 , R. Santhi 4 and N. Sathiah 5 1

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One of the major components in precision agriculture is crop health monitoring, which includes irrigation, fertilization, pesticide sprays, and timely harvest of the crop. Further, the progressive change in growth and development is critical in crop monitoring and taking suitable decisions to maintain health status. In order to accomplish the task, drones are highly useful for on site detection of problems so as to undertake corrective measures instantly. Although it is expensive to build algorithms and establish relationships between ground truth and spectral signatures, it is a user-friendly technique once the basics studies are done. As labor availability and technical manpower are extremely limited, particularly in India, drones are gaining popularity in the context of smart farming. Insect pests are known to cause catastrophe and drastic reduction in food grain production across the globe. The losses that have been predicted by FAO is over 37% due to pests and diseases. Recently, crops cultivated in India have been threatened by invasive pests like fall army worm (Spodoptera frugiperda) in corn and Rugose spiraling whitefly in coconut (Aleurodicus rugiperculatous Martin); these pests caused extensive damage during the years 2018 and 2019. The plant protection measures are to be taken on a community basis so as to ensure effective management of pests. In India, more than 80% of farmlands are in the category of small and marginal (<1 ha), so it is very difficult to manage the invasive pests. If one field is sprayed, the pests simply shift their feeding to the neighboring fields. To address this, drones become essential. Drones are unmanned aerial vehicles exploited in a wide array of disciplines such as defense, monitoring systems, and disaster management but are only beginning to be utilized in agricultural sciences. There are three major types of drones, namely fixed wing, multi-rotor, and hybrid type, and the usage depends on specific applications. The other types depend on degree of automation, size, weight, and power source. The set operational parameters such as flight speed, height, and endurance need to be optimized to use drones appropriately in agriculture and allied sectors. In addition, parameters related to drone-based spraying such as droplet size, spread, density, uniformity, deposition, and penetrability should also be factored in when implementing drone-based mitigation strategies. Despite the fact that drone technology is highly relevant and appropriate for pest management, the adoption of the technology is restricted. Regulatory guidelines have been set across the globe to perform site-specific farm management with higher precision at a very high resolution. Overall, drones can be employed in almost all agricultural field operations and are considered excellent

tools for rapid, reliable, and non-destructive detection of field problems. This review provides panoramic views of drone technology and its application in the management of pests in a digital agriculture era. Keywords: unmanned aerial vehicle, drone technology, pest management, sensors, precision agriculture

INTRODUCTION

Shamshiri et al., 2018). The agricultural research institution State Department of Agriculture have devoted attention to designing and fabricating drones that suit Indian conditions. The design of UAVs should consider various parameters such as droplet size, wind speed, flight speed, and flight height (Zhang et al., 2012, 2015; Qin et al., 2014). Further, meteorological parameters like wind speed, temperature, and relative humidity can affect the efficacy of pesticide sprays under field conditions (Wang et al., 2018). Under natural conditions, it is

very difficult to control the meteorological parameters and thus scientists have attempted to study the drones under protected conditions. Lv et al. (2019) have examined the efficacy of drones under a protected environment in order to prevent the external interference and the impact of drone flying speed on droplet size, shape, distribution, and uniformity. The study is very useful in optimizing various parameters to determine the effective spray of pesticides using drones. One of the most important criteria for the successful delivery of pesticides or any other input is droplet size. Lv et al. (2019) have conducted a series of elegant experiments to set the parameters for drones to enable pesticide spray and its impact on crop productivity.

The biotic stresses caused by pests and diseases are well-known to cause devastation that results in reductions in global food grain production. The FAO has predicted that the losses due to pests and diseases are over 37% (Cao, 2015). They are also severely affecting the crop growth, yield, and quality of produce (Gossen et al., 2008; Berger-Neto et al., 2017). Recently, crops cultivated in India are being threatened by invasive pests such as fall army worm (Spodoptera frugiperda JE Smith) in corn and Rugose spiraling whitefly in coconut (Aleurodicus rugiperculatous Martin), causing extensive damage during 2018 and 2019 (Lal and Bikram, 2019). The fall army worm has become a serious matter of concern to the farmers of India, first hitting the Indian subcontinent in May 2018 in the State of Karnataka. The Indian Agricultural Research Institute–Natural Bureau of Agricultural Insect Resources estimated the intensity of infestation to the tune of 9–62% with an economic yield loss of 34%. The incidence of FAW has spread to the neighboring state of Tamil Nadu where more than 20 districts out of 38 were badly affected in 2019. The effective and rapid interventions and implementation of strategic work plans included drone technology that helped to lessen the incidence of FAW and protect maize crop from infestation while ensuring crop productivity. These pests are to be meticulously monitored and proper technology capsules are to be adopted to save the crops from devastation. Several plant protection strategies are being followed in an integrated way to ensure that crops are protected during the entire crop growing season. The plant protection measures are to be taken on a community basis so as to ensure effective management of pests and diseases. In India, more than 80% of farmlands are in the category of small and marginal (<1 ha), so it is very difficult to manage invasive pests. If one field is sprayed, the pests simply shift their feeding to the neighboring fields. The invasive pests have enormous potential to multiply in an alarming proportion and are almost impossible to manage with conventional methods of plant protection strategies. It is reported that the annual global use of plant protection chemicals against trans-boundary pests was more than 3 billion kg (Heidary et al., 2014). The utilization of pesticides that are sprayed on the crops exceeds 20–30% and the remaining 70–80% goes as run-off, leaching, evaporation, and drift that cause soil and aquatic pollution as well as deteriorating the quality of the crop produce (Markle et al., 2016; Torrent et al., 2017). Under these circumstances, effective and timely spraying of plant protection measures are very important. For this, miniaturized unmanned aerial vehicles possess a wide array of benefits that include high efficiency, reduced labor requirement, saving of time and energy, quick response time, and vast area coverage, as well as environmental safety (Meng et al., 2018;

DELIVERY OF DROPLETS One of the critical factors to be considered for the effectiveness of drone-enabled spray is droplet deposition. The parameters used for measuring the effectiveness of droplet deposition include density, area coverage, and arithmetic mean of droplet size and variation coefficient (Zhu et al., 2011). The droplet deposition density is defined as the number of droplets deposited per unit area which is often measured using blotting paper. Droplet deposition coverage is yet another parameter usually recorded for assessing effectiveness, and is the area of all droplet particles deposited per unit area (Cunha et al., 2012). The arithmetic mean droplet size is the average value of all droplet diameters in one spray sample (Fan, 2011). The co-efficient of variation (CV) measures the uniform spread of droplet deposition in an aerial spraying operation. These four indices can be calculated using the formulae outlined below: a. Droplet deposition density (D) No. of droplets deposited (n)/area of droplet collection material (A) b. Droplet deposition coverage (C) Area of droplet deposition (S)/Area of the blotting paper (A) c. Arithmetic mean of droplet size (D0) = Σ Di Ni/Σ Ni Di is the droplet diameter over time interval Ni is the number of droplets over time interval d. Co-efficient of Variation (CV) = SD/X

StandardDeviation(SD) =

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s

Pn

i=1 (xi − u)

2

n− 1

Xi is the droplet deposition particle size per unit area of blotting paper. μ is the average droplet size per unit area of blotting paper. SD is the standard deviation. n is the number of droplets per blotting paper. When the CV is smaller, the distribution is considered as uniform, the spray covers the target area, and improves the effectiveness of the sprayed pesticides. FIGURE 1 | Quadcopter imaging rice fields to determine the health status using infrared imaging.

INFRARED THERMAL IMAGING Thermal imaging is a technique to improve the visibility of the reference objects in a dark environment by detecting it using infrared radiation and creating an image based on the information. Thermal imaging, near-infrared illumination, and low-light imaging are the three most commonly used night vision technologies. Infrared thermal imaging can be exploited for assessing the droplet size and distribution in drone-enabled pesticide sprays. Lv et al. (2019) have used the infrared thermal imaging technique to accurately measure droplet deposition. After the drones spray, there will be changes in leaf temperature and the infrared thermal imaging technique detects infrared-specific band signal of object thermal radiation by optoelectronic technology, which was used as a supplementary means for droplet deposition measurement. In order to avoid external interference, closed environmental chambers can be employed along with the acquisition of thermal images after the spray test. With a view to prevent changes in temperature before and after spraying, sampling can be done in the middle of the fields using infrared thermal imaging (Lv et al., 2019). A classic method developed by Lv et al. (2019) can be employed to determine droplet deposition with the drones. They have optimized the droplet density, deposition coverage, and droplet size decreases with the drone flight speed. Their studies further inferred that the infrared thermal imager is highly useful for assessing the droplet deposition in the farm drone-enabled spraying. The Tamil Nadu Agricultural University, India, has initiated work on infrared imaging of rice fields using a quadcopter attached with a sensor in order to monitor the health status of the plant (Figure 1).

spraying as the leaves of the rice canopy overlap (Sheng et al., 2002). Further, BPH often colonize at the lower part of the plant which is inaccessible through a manual sprayer. In addition, the muddy fields and overlapping plants makes the conventional system of pesticide spray difficult. In order to overcome the bundle of practical difficulties and acute labor shortage, aerial spray of pesticide using UAVs becomes inevitable (Zhou et al., 2013). Qin et al. (2016) have explored the possibility of using a miniaturized UAV for pesticide spray with high efficiency with no damage to the rice crop in hilly areas of China. They found that the deposition and distribution of droplets increased with the progression of rice growth which synchronizes with operational height and velocity of crop spraying as executed by the UAV. They have standardized flying height (1.5 m) and speed (5 m s−1) that provides effective delivery of pesticides at the lower leaf as well as uniform distribution (CV = 23%). This also registered an insecticidal efficacy of 92–74% from 3 to 10 days after spraying insecticide. Qin et al. (2016) have offered a strong data base for the optimized design, improved performance, and rational application of UAV in spraying insecticide in rice fields. The range of drone flying height (0.8 and 1.5 m) and flight speed (3 and 5 m s_1) have shown distinct performance in the deposition of droplets. Since the BPH stays in the bottom of the leaves, increased spraying height and speed can enable effective delivery of pesticides and control of pests. Overall, the study has clearly shown that UAV spraying exhibited a superior efficiency than the conventional stretcher sprayer, especially when operated at an altitude of 1.5 m and a velocity of 5 m s_1 . Moreover, even 5 and 10 days after pesticide application, a high controlling efficiency was still observed, indicating that the spraying method of low volume and high concentration enhanced the duration of pesticide activity. Recently, the Tamil Nadu Agricultural University, Coimbatore, India, made a maiden attempt to study the efficacy of pesticide spray (fungicide copper oxychloride 53.8% @ 35 g 16 L−1 against bacterial and fungal diseases) in rice fields using drones during the cropping season of September 2020. A hexacopter type drone (payload 16 L; fuel capacity 3.5 L) was employed to study the application of pesticides in rice fields

RICE Aerial Spray for Brown Plant Hoppers in Rice Rice is a staple food crop for more than 2.7 billion people in Asia; the loss of productivity of the crop has been estimated as more than 20% (Brookes and Barfoot, 2003). The brown plant hopper (BPH) Nilaparvata lugens causes considerable loss of crop yields globally and is a major pest in India in the late season rice crop planted during September–October (Zhang et al., 2011). The BPH causes damage at the late stage of rice growth. During the late stage of the crop, it is very difficult to undertake manual

of pesticide use, optimal meteorological parameters are set in a standard operational protocol for drone-enabled spray of agrochemicals. The optimal flight height of 1.5–2.0 m, flight speed 5 m s−1 , in combination with wind speed of below 5 km h−1 was found to be effective for spraying pesticides with drones. Lou et al. (2018) have established a relationship between CV of droplet distribution and flight heights of UAV in cotton fields. Their studies have shown that the co-efficient of droplet densities in the upper, middle, and lower layers of the cotton canopy were at 1.5 m (117.1, 178.1, and 85.8%) and 2.0 m (79.4, 50.3, and 146.4%), respectively. The CV of upper and middle droplet densities at the flight height of 1.5 m was significantly higher than 2 m. It is observed that the reduced flight height, which generates a strong downward swirling airflow that causes the plants to sway substantially and affects the droplet density, causes a significant change of the cotton canopy (Qin et al., 2014). In the study, the droplets' distribution in the vertical direction was considered as density of the droplet. The coverage at the drone flying altitude of 1.5 m (2.5, 3.2, and 1.9%) and 2 m (4.9, 5.5, and 5.0%) were on the upper, middle, and lower layers of the cotton. The spread of the pesticide was more effective in 2 m than 1.5 m. As the flight height increases, the downward pressure gets weakened with wind field below the rotor. There may be a small portion of drift which may be associated with the lateral wind effects.

FIGURE 2 | Hexacopter spraying pesticides in rice fields of Tamil Nadu Agricultural University Farm in Tamil Nadu, India during October 2019.

(Figure 2). Preliminary studies have shown the optimal flying height (3 m), speed (5 m s−1), swath (4 m), and the area coverage (4 min acre−1). The literature review in combination with the preliminary data from Tamil Nadu Agricultural University, India, clearly demonstrate that drone-enabled pesticide spray is an emerging potential technology to overcome labor shortages and to carry out plant protection measures without loss of time.

Aerial Spray of Pesticides on Aphids and Spider Mites in Cotton

COTTON

In cotton, aphids and mites are serious sucking pests of great concern that cause extensive damage to the crop (Lou et al., 2018). In order to address these pests, aerial sprays using drones were attempted. Lou et al. (2018) studied the efficacy of unmanned aerial vehicles (UAVs) on cotton aphids and spider mites. Similar to other literature, they too recorded that droplet uniformity, spread of the pesticide, and deposition were higher at a flight height of 2 m. The control of aphids and spider mites in cotton were registered as 63.7 and 61.3%, respectively, and the efficacy was lower than boom spraying. They also observed that the UAV spray was slightly less effective in comparison to boom spraying due to the spiral arrangement of leaves in cotton. These data serve as the basis to determine the theoretical prediction of the pesticide effectiveness in cotton fields using drones.

Cotton is predominantly cultivated in Australia, Pakistan, India, China, Brazil, and the USA, constituting 80% of the global cotton produced (https://www.wto.org/english/news_e/ news16_e/cdac_01jul16_e.pdf). The crop is badly affected by a wide array of defoliating, boll feeding, and sucking pests that devastate the crop to the tune of 10–80% (Sharma et al., 2017). In order to protect the crop from insect pests, huge quantities of pesticides have been used in the past several decades. Indeed, cotton crop alone accounts for 16% of pesticides used globally (https://ejfoundation.org/resources/ downloads/the_deadly_chemicals_in_cotton.pdf). This led to the introduction of Bt cotton to reduce the pesticide use to some extent (Krishna and Qaim, 2012). As cotton is

cultivated in contiguous blocks, there is every chance that the insect pests will shift their habitat if neighboring fields are sprayed. This situation warrants drone spray to enable a quick response and protect the crop from devastation. There are a few classic works that are summarized below.

CHILLIES The chilly crop is badly affected by pests and diseases causing yield reduction to the tune of 30–40% (Zhang et al., 2013). One of the most dreadful diseases is the Phytophthora capsica, the causal organism for Phytophthora blight in pepper, which shows typical symptoms in the roots, stems, leaves, and fruits, and causes deadly diseases throughout the world (Hausbeck and Lamour, 2004). The spread of the disease is very quick and rapid action is required to contain the disease at the early stage of incidence (He et al., 2019). Yet another sucking pest, Aphids Aphis gossypii Glover, is equally as devastating and reduces crop yield drastically. Aphids suck the plant sap of pepper plants, causing the leaf to curl and its associated honeydew

Droplet Drift, Deposition, and Distribution Pattern The unmanned aerial vehicles (UAVs) performance is often affected by environmental factors such as wind speed, direction of wind, temperature, and rain. When spray is undertaken with drones, a small portion of the dosage does not reach the target area, which is popularly referred to as droplet drift or spray drift (Kirk, 2004). Such drift in pesticides is closely associated with wind speed and direction. In order to reduce the drift and wastage

secretion attracts sooty mold infestation, leading to reduced photosynthesis and yield reduction (Chen et al., 2018). In order to address these devastating pests and diseases in chillies, recently, Xiao et al. (2020) have used drones to contain them effectively, rapidly, and with good time management.

TABLE 1 | Drone spray parameters. Indices

Flying height (m)

Flight velocity (m/s)

Deposition density

Droplet Coverage and Density Droplet coverage is crucial to measure the effectiveness of drone spray. Xiao et al. (2020) have compared the droplet coverage rate of the electric air-pressure knapsack (EAP) sprayer with drone spray. They found that the EAP coverage was twice as high than that of UAV-enabled spraying of pesticides (21.12 vs. 1.83% and 18.59 vs. 1.43%). Such reduction in coverage closely coincided with the spraying volume of the EAP sprayer (300 L/ha), which was 20 times that of the UAV sprayer (15 L/ha). The results clearly demonstrate that the coverage of pesticide is positively correlated with spray volume. With the progression of plant growth, the droplet coverage was lower in the middle and lower part of the plant in comparison to the first spray. As the leaf area index of the chillies increases with the advancement of growth, the droplet coverage decreased progressively. On the other hand, when double spraying was done, both the upper and middle parts of the plant had better droplet coverage in drones spray as well as EAP (Xiao et al., 2020). Scattered growth within the plants affects the spray fluid penetration in the plants (Zhu et al., 2004). In chillies, there are several pests and diseases that occur in the lower part of the plant and that can be effectively controlled only through droplet penetrability (Wang et al., 2019b). This study further suggests that the penetration of droplets from the UAVenabled spray is still worse than an EAP sprayer. Spray deposits decreased from the top to bottom of the canopies and decreased linearly with the increase in leaf area index. Droplet density is also equally important to determine the effectiveness of the drone-enabled spraying (Yuan and Wang, 2015). Xiao et al. (2020) established a relationship between the spray volume and droplet intensity. Spray volume has a remarkable impact on the droplet size and the increasing spray volume increased the droplet intensity. The droplet density of upper, middle, and lower part of the chillies plants and the ground were 34.91, 23.03, 15.06, and 9.50 cm−2 , respectively, while EAP had twice as high droplet intensity regardless of the position of the plant. The uniformity of the deposition is also very important for controlling pests and diseases. The uniformity is better in upper layers of the plant canopy than that of the middle and lower layers. Further, such measurements

decreased with the progression of crop growth due to expansion of the canopy spread area and leaf area index. In addition to the droplet density, distribution, and uniformity, penetrability of the pesticides is very significant in determining the efficacy of UAV-enabled spray (Xiao et al., 2020). The pest and disease control efficiencies of both EAP sprayer and drone spray were critically evaluated. Xiao et al. (2020) have shown that the control efficiency of drone spray was more effective only when one-third of the concentration of pesticide was used in comparison to the conventional spray. Since EAP sprayer had better deposition and uniformity, the control of processing peppers with P. capsici was more effective. Similarly,

Spray fluid (L ha−1)

Upper

15

3

4

Middle

15

2

4

Lower

15

2

4

control of aphids was also better in EAP than in UAV spraying. These data clearly demonstrate that drone spray has the potential to reduce the pesticide use, which is safer and reduces the cost to farmers.

SUGARCANE Sugarcane is widely cultivated in tropical countries and India is one of the leading producers and consumers of sugar. In the past decade, areas producing sugarcane have declined drastically, particularly in Tamil Nadu, where the area under sugarcane reduced from 5 lakh ha to <1 ha in the past 5 years. One of the prime reasons for such a phenomenon is the requirement of labor and mechanization which is very scarce (Huang et al., 2014) (Table 1). During the cropping period, any intercultural spray pesticides, nutrients, or bioinoculants are extremely difficult due to the morphology of the crop and sharp edges of the leaf blades which often injure workers (Gebregiorgis, 2012). Further, some of the pests (internode borer, top borer) diseases (smut, red rot, yellow leaf disease) are highly devastating and farmers find it difficult take up any plant protection measures. Under these circumstances, drones may be of help to deliver sprays in sugarcane fields (Lan et al., 2017).

Optimal UAV Parameters for Sugarcane Sugarcane is a long duration crop, and the canopy arrangements are different from other crops. Aerial spray by drones may be advantageous as accessibility to the cropped field is very difficult in sugarcane (Zhang et al., 2011). Use of UAV in sugarcane is very limited. Zhang et al. (2020) conducted experiments to optimize various spray parameters (spray volume, flight height, and flight velocity) and three levels by quad-rotor drone. The results revealed that with a comprehensive consideration of the density, uniformity, and penetration of droplet deposition, the optimal spraying parameters were 15 L/ha of spray volume, 3 m of flight height, and 4 m/s of flight velocity, which could be used as a reference parameter for drones when applied in sugarcane crop.

Drones to Manage Fall Army Worm in Sugarcane The Fall Army Worm (Spodoptera furgiperda) is one of the invasive pests causing extensive damage in maize (Ganiger et al., 2018). The pest, originally from the USA, migrated to Africa in 2016 and entered southern India in 2018 (Padhee and Prasanna, 2019). It is a polyphagous pest that feeds on a wide range of cereals, millets, sugarcane, banana, and other crops (Khan et al., 2018). It causes extensive damage in a very short span of time.

5

No

Crops

Pesticide

UAV type

Flight height (m)

Flight speed (m/s)

Nozzle type

Spray drift (%)

Efficiency/area covered Comments

1

Rice

Pesticide

Four-rotor electric UAV

Maximum 1–6

Maximum 0–8

–

–

–

UAV single rotor drone

1.5–3

2 3

Rice Rice

Pesticide

Plant Protection Six-rotor UAV

References

– Guo et al., 2019

3.5

3–6 Maximum 10

Hollow cone, flat cone

–

–

–

–

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TABLE 2 | Application of UAVs with the set of parameters (Flight height, Flight speed, Nozzle Type) for pesticides spray in various crops and their efficiencies in comparison to conventional sprayers.

– Li et al., 2019

–

– Yang et al., 2017

4
5
Rice
Rice
–
Tebuconazole
Wind Speed Sensor Network measurement system (WWSSN) UAV
0.98
Single rotor UAV
2
3.2
5
–
–
Flow of single nozzle/L/min −0.80
–
Droplet deposition in effective spray area 76.45%
–
High efficiency of UAVs is not fully achieved
Liquid distribution was un-uniform due to application of Pesticide in UAVs and low precision level
Chen et al., 2017
6
6
Rice
Pesticide
Single rotor UAV
1.5
5
TEEJET nozzle
–
High control efficiency
UAV was more effective against plant hoppers
7
Rice
Pesticide
Multi rotor UAV
1.5
5 with 1.9~2.5 wind speed
TEEJET nozzle
23.06
–

Droplet deposition uniformity, 21.62%

1

Flat fan nozzle 4 nos.

5

8

Rice

–

UAV

1

Spray uniformity 98.5%

Field performance in paddy crop was found to be 1.08 ha/h

Wang et al., 2017

Qin et al., 2016 Chen et al., 2020 Yallappa et al., 2018

Rice

Fluorescent dye UAV Rhodamine-B

5

3

Two fan nozzles

90% drift within 8m

92.8%

Using the low altitude helicopter, droplets can Xue et al., 2014 penetrate and liquid deposition occurs to the lower part of crops

10

Small bell stage Corn

Plant Protection UAV

1

4

Two fan nozzles

–

–

–

Corn

Plant Protection UAV

11

Zheng et al., 2017 2

2

Two fan nozzles

–

–

– Zheng et al., 2017

12

Wheat

Pesticide

UAV

2

5

3 nozzle

–

effective spraying width was 5 m 16.8 L/ha@0.4 MPa

UAV and EAP performance were compared. Low volume with fine nozzle was better than coarse nozzle with high volume

Wang et al., 2019b

(Continued)

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9

No

Crops

Pesticide

UAV type

Flight height (m)

Flight speed (m/s)

Nozzle type

Spray drift (%)

Efficiency/area covered Comments

13

Wheat

Fungicide

UAV

5

4

Rotary atomizer – nozzle Low volume and high concentration

Droplet distribution was uniform and the CV was 33.13%. Control efficiency reached 55.1%

Droplet deposition was higher in lower layers of wheat than the upper layer by about 45.6%

References

Qin et al., 2018

14

Cotton

Defoliation 540 g/L thidiazuron and diuron SC: 180

UAV Spraying volume (L/ha) 15.0–22.5

2

≤5

–

–

–

Bolls opened in Shihezi and Hutubi experimental Meng et al., 2019 sites are 40.74 and 36.90%, respectively.

15

Cotton

Pesticide

ASPEE with maximum Psi up to 1,400 kPa,

–

0.8333

11 m boom sprayer

–

Field efficiency 63.03%

Uniformly distributed in 600 kPa Psi with swath width of 1,235. The average theoretical field capacity was 3.3 ha/h and the average effective field capacity was 2.08 ha/h.

UAV

1.5

4 nos centrifugal nozzle

5–15

16

Cotton

Pesticide

–

Effectiveness against aphids and spider mites were 63.7% and 61.3%, respectively

The droplet uniformity and deposition were satisfactory

Subramanian et al.

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TABLE 2 | Continued

Hunt, 1983; Sanchavat et al., 2018

Lou et al., 2018

7

Groundnut

–

UAV

1

1

Flat fan nozzle 4 nos.

5

Spray uniformity 98.5%

Field performance in groundnut was found to Yallappa et al., 2018 be 1.15 ha/h

18

Soybean

Pesticide

Medium-quality sprays

–

–

Flat fan nozzle

–

Spray fluid 145 L/ha

Fine-quality sprays Derksen et al., should be avoided for 2008 treating lower portions of a canopy unless some other form of energy, such as air-assistance spray, will help move deeper into a canopy.

19

Sugarcane

Pesticide

Quad-rotor drone

3

4

Positioning system and centrifugal atomizing nozzle

–

–

Drone application efficiency can be 60 times higher and spray fluid application rate is 20–30% lesser than conventional spray

Zhang et al., 2019

(Continued)

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17

No

Crops

Pesticide

UAV type

Flight height (m)

Flight speed (m/s)

Nozzle type

Spray drift (%)

Efficiency/area covered Comments

20

Sugarcane

Pesticide

UAV

3

3

–

–

Control efficacy against Fall Armyworm (Spodoptera frugiperda) applied with chlorfenapyr–chlorantraniliprole– lufenuron were 94.86 and 94.94%, respectively

Highly efficient and flexible and has been successfully applied in sugarcane

21

Sugarcane

Stem Borer (Lepidoptera)

Multi-rotor UAV

22

Pineapple

Pesticide

UAV < 2.5 Oil driving single rotor Droplet size/μm−268.6 Flow rate single)/mL/min−800

Pineapple

Pesticide

24

Tea

Pesticide

25

26

Centrifugal atomizing nozzle

–

spray efficiency was 21.3 min/ha pesticide need is lesser than 90.65% compared to conventional spary

UAV spray was found to Zhang et al., be 40.0%, which was 2019 higher compared to knapsack electric sprayer KES (30.0%)

1.14–2.82

–

11 to < 26.44%.

90% spray drift distance can control in 10 m.

Effectively control the spray drift.

90% spray drift distance can be up to 33.54–46.50 m.

Total spray drift percentage also increased.

Coverage 26.8%

Increase of the UAV flight speed resulted decrease in droplet distribution uniformity.

Upto 3.5

2.02–3.59

–

UAV simulation platform

2

0.3

Four VP110015 flat-fan nozzles

Phytophthora capsici
UAV
2
Aphis gossypii
UAV
55.76%
Pepper
Grassland
5% urea aqueous solution
Helicopter
2
2
–
–
4
–
–
hydraulic CP flat nozzles
–
–
–
Electric Air-Pressure Knapsack EAP 21.12% vs. UAV 1.83% Less
UAV sprayer (15 L/ha) Efficiency was higher since 20 times lesser than that of the in EAP sprayer (300 L/ha)
Less
UAV sprayer (15 L/ha) Efficiency was higher since 20 times lesser than that of the in EAP sprayer (300 L/ha)
62.83%
Wang et al., 2018
Lv et al., 2019
Xiao et al., 2020
Xiao et al., 2020
– Yao et al., 2020 (Continued)
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27
Pepper
Lan et al., 2017; Song et al., 2020
4
8
23
3
References

TABLE 2 | Continued
TABLE 2 | Continued Crops
Pesticide
UAV type
Flight height (m)
Flight speed (m/s)
Nozzle type
Spray drift (%)
Efficiency/area covered Comments
28
–
Pesticide
Single rotor UAV
3
5
Two flat standard nozzles
–
–
Rotary Atomization sprayer
–
29
30
–
–
Pesticide
–
UAV
Octocopter
–
3
–
1
Wang et al., 2016 –
Extended-range Less flat-spray nozzles
30–60%
Rotary Atomization sprayer is more suitable for low-volume and variable-rate spraying, both are not possible with hydraulic nozzles.
Joseph et al., 2019
–

–

Octocopter

3

3

Extended-range more flat-spray nozzles

13–22%

–

32

–

Pesticide

Six symmetrically positioned rotors

0.6

1.3

Flat fan nozzle with 0.2 MPa Psi

–

–

–

Unmanned helicopter

–

Rotary nozzles

–

–

Pesticide

2.2

Gong et al., 2019

–

31

33

References

Bogusława and Jerzy, 2017 –

Precision nutrient management

Huang et al., 2014

–

Plant protection UAV

5

–

Two centrifugal rotary atomizers

–

spraying swath 5 m, their coefficient 41%

The Standard for Xue et al., ultra-low volume 2016 spraying variation coefficient, which is less than 60%

35

–

–

Single-rotor Unmanned Agricultural Helicopter

–

0.5

Centrifugal atomization nozzles

–

Downwash covers approximately a circle area of 3.0 m radius

–

UAV

–

–

–

–

–

–

9

34

36

–

Pesticide

2

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No

Zhang et al., 2017

Zhang et al., 2019 –

Pesticide

UAV

6

2.2

– Four spray nozzles, Micronair Ultra-LowVolume (ULV) nozzles

30 m (100 ft) effective spray swath and able to spray 0.4 ha/min (1 acre/min)

Drone spraying is Huang et al., excellent for vector control (<50-μm droplet 2009 size)

38

–

–

Fixed-wing applications

0.35 m

Wind speed 0.084 (120–305 km/h)

Flat fan nozzle

–

The increment of the tube pressure will strongly decrease the droplet diameter at a lower wind speed and vice versa

–

Tang et al., 2016

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Drones in Insect Pest Management

In order to control the pest, quick action has to be taken to ensure that pest population is kept at bay. Drones are highly useful technology to undertake spray quickly to contain the pest population. Song et al. (2020) have shown that the application of chlorfenapyr–chlorantraniliprole–lufenuron through drones had control efficacy of 94.94% and declined the pest population by about 94.86%.

- Drone efficiencies are to be examined for certain application parameters such as droplet size distribution, droplet coverage, uniformity of droplets, droplet penetrability, droplet drift, and insecticidal efficiency prior to commercial use of drones in agriculture (Lv et al., 2019). 5. There are potential benefits to drone usage in agriculture that include large area coverage, less quantities of pesticides, labor saving, quick response time, and timely operation well before pest occurrence exceeds economic threshold levels (Huang et al., 2018). 6. Despite the fact that there are ample advantages attached to drone technology, every country has its own regulatory guidelines for the use of drones in agriculture (Ayamga et al., 2021). Prior approvals are required from local authorities to use drones in agriculture.

CONCLUSION An extensive review was undertaken to determine the feasibility and utilization of Unmanned Aerial Vehicles (UAVs) or drones for pesticide sprays in various crops; the output from the literature is summarized in Table 2. The table clearly suggests that there are several studies that have been undertaken and demonstrated on the use of drones successfully in pesticide spray in agricultural and horticultural crops. The following are the observations:

Overall, the literature review clearly demonstrated that drone technology is very effective in delivering pesticides for a wide array of crops. The effectiveness has been validated with conventional hand-operated sprayers. The data suggest that, although the operational parameters and delivery parameters have been optimized for a specific crop or a particular pests/disease, some fine tuning is required to improve the efficacy for a given situation. This literature review has given an overview of drone technology employed for pesticide sprays. Since there are no ultralow volume pesticide formulations available in the market, the conventional pesticides were used in drone technology with the same optimized concentration. Thus, there is an urgent need to develop innovative new nano formulations to improve the efficacy of drone technology while minimizing the cost and improving environmental safety.

- Drone application in agriculture is primarily focused on pesticide applications. Extensive research has been done on optimization of spray volume, droplet size, spread of droplets, and penetrability as well as efficacy of pesticides in insect pest control (Lou et al., 2018). Many of the optimization parameters indicated were done mainly for pesticides use in agriculture. 2. A majority of the research on UAV for pesticide spray in crops was carried out in rice (Qin et al., 2016), wheat (Wang et al., 2019a), corn (Zheng et al., 2017), cotton (Lou et al., 2018), pepper (Xiao et al., 2020), and sugarcane (Zhang et al., 2019) as these crops consume more pesticides than any others. Further, these crops are cultivated in larger areas in contiguous blocks in developed and developing countries where drone application is feasible. 3. In order to improve insecticidal use efficiencies in crops, drone operational parameters such as flight speed, flight height, nozzle type, payload, and drone type are be optimized for the given situation. Overall, flight height of 2–3 m, flight speed of 3–5 ms−1 , two fan nozzle, four rotor UAV, and 15 L payload are found to be optimal to undertake pesticide sprays using drones in agricultural crops (Zhang et al., 2011).

AUTHOR CONTRIBUTIONS KS: synthesis and orchestration of the review. SP: responsible for drones enabled application. GS: collection of literature and plagiarism check. RS: drone application in agriculture. NS:

entomologist involved in drone enabled spray. All authors contributed to the article and approved the submitted version.

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Improving agricultural spraying with multi-rotor drones: a technical study on operational parameter optimization D. Yallappa 1, R. Kavitha 1*, A. Surendrakumar 1, B. Suthakar 1, A. P. Mohan Kumar 1, Balaji Kannan 2 and M. K. Kalarani 3 Department of Farm Machinery and Power Engineering, Agricultural Engineering College and Research Institute, Tamil Nadu Agricultural University, Coimbatore, India, 2 Department of Soil and Water Conservation Engineering, Agricultural Engineering College and Research Institute, Tamil Nadu Agricultural University, Coimbatore, India, 3 Directorate of Crop Management, Tamil Nadu Agricultural University, Coimbatore, India 1

Drones play a key role in enhancing nutrient management efficiency under climate change scenarios by enabling precise and adaptable spray applications. Current aerial spray application research is primarily focused on examining the influence of drone spraying parameters viz., flight height, travel speed, rotor configuration, droplet size, payload, spray pressure, spray discharge and wind velocity on spray droplet deposition characteristics. The present study aimed to study and optimize the effect of spray height, operating pressure, nozzle spacing and spray nozzle mounting configuration on spray discharge rate, spray width, spray

distribution pattern, spray uniformity and spray liquid loss. A spray patternator of 5.0 m x 5.0 m was developed per Bureau of Indian Standards (BIS) standard to study the spray volume distribution pattern of boom and hex nozzle configuration. Initially, drone spray operational parameters viz., spray discharge rate (Lm−1), operating pressure (kg cm−2) and spray angle (°) were measured using digital nozzle tester, digital pressure gauge and digital protractor, respectively, in the laboratory. Then optimized the nozzle spacing for boom configuration attachment to drone sprayer and recorded best spray uniformity at 0.6 m nozzle spacing. The drone sprayer hovered at three different heights, viz., 1.0, 2.0 and 3.0 m from the top of the patternator and spray operating pressure was maintained at 4.0 kg cm−2 in outdoor condition. Single pass distribution pattern and onedirection application distribution pattern method used for optimizing height of spray, operating pressure and nozzle mounting confirmation from the results of discharge rate, spray angle, effective spray width, spray liquid loss and spray distribution uniformity. Results showed that, the better spray uniformity distribution was found when the drone sprayer hover height was increased from the top of the patternator (2.0 m). More round spray droplet vertex pattern was generated during the 1.0 m hover height compared to the 2.0 and 3.0 m hover heights due to the direct impact of downwash airflow generated by the rotors. Finally it was concluded that, the good spray volume distribution was found at 2.0 m height of spray with standard hexa nozzle configuration arrangement as compared to the boom spray nozzle arrangement. KEYWORDS

boom spray, discharge rate, drone sprayer, distribution pattern, hover height, patternator

1 Introduction

The overall goal of this research was to develop a suitable size patternator for measuring, analyzing and optimizing the spray operational parameters of drone sprayer with the specific objectives viz., (1) development of a suitable customized spray patternator for measuring spray pattern distributions; (2) evaluation for optimizing the effect of height of spray, nozzle spacing and operating pressure on spray discharge rate, effective spray width, spray angle, spray uniformity and spray volume distribution pattern (3) investigation on the impact of drone sprayer machine parameter as downwash airflow on spray distribution systems at different hover heights in outdoor conditions. (4) Recommending the best spray nozzle configuration to drone sprayer based on the spray volume uniformity distribution before actual use in field condition. Optimizing the spray operational parameters of multi-rotor agricultural drones is crucial for accurately estimating and enhancing crop resilience. By delivering precise, timely, and efficient applications, these drones support the development of stronger, more resilient crops, ultimately contributing to sustainable agricultural practices and improved food and nutritional security.

Technological advancements in precision farming, especially through the integration of multi-rotor drones with sprayer devices have revolutionized agricultural practices. These drones enable precise and targeted nutrient management, enhancing crop efficiency and resilience in the face of climate change, thus have transformed pesticide, herbicide, and fertilizer applications (1, 2). These drones provide precise, targeted pesticide delivery, reducing waste, lowering environmental impact, and boosting overall crop health (3). The efficiency of these drone sprayers, however, is strongly reliant on the optimization of their operational parameters. Spray height, nozzle type, droplet size, flight speed, and application rate must all be precisely adjusted to guarantee even coverage and successful pest control. Optimizing these parameters is crucial not only for maximizing the efficacy of the chemicals used, but also for preserving and improving crop nutritional quality. Drones have greatly become benefited with advanced features in autonomous spraying systems, including autonomous path planning, break point continue to spray (4), terrain following radar module (auto altitude adjustment), highprecision obstacle avoidance radar, spray task list, spray solution empty indication, battery level warning, and high-accuracy Real Time Kinematics (RTK) location to significantly increase functional stability, efficiency, accuracy, and ease of use (5). Nutrient composition is directly influenced by the right executive management of nutrients and protective agents, which aids in crop development (6, 7). For example, uniform and optimal spraying can guarantee that crops receive the proper amount of nutrients,

resulting in improved growth and nutrient buildup in edible sections of the plant. Furthermore, accurate spraying can reduce crop stress from pests, diseases, and environmental conditions, increasing their resistance. Stress resilience, another important element of crop health, can be strongly influenced by the efficacy of pesticide use. Crops that are less stressed grow faster, produce more, and have superior nutritional profiles. The drone machine operational parameters, viz., flight height, travel speed, payload and configuration, have a great impact on the distribution and penetration of droplets (8). The most important benefit of using a drone (multi-rotor) for chemical spraying is that, due to its unique rotor structure and principle of motion, it generates powerful downwash airflow during flight operation, changing the crop disturbance and improving liquid penetration (9). The downwash airflow velocity of the rotors can create a strong velocity distribution of plants during spraying. This helps the spray droplets to atomize much further with enhanced deposition onto the crop surface. Spray droplet velocity has positive effects on spray swath, deposition, and drift, influencing the operation's consequences (10). Yallappa et al. (11) studied spray volume distribution pattern for boom nozzle configuration using drone sprayer under laboratory condition. There is lack of detailed study regarding performance of spray operational parameters viz., height of spray, spray pressure, travel speed, discharge rate, spray droplet distribution uniformity and spray nozzle spacing for efficient chemical spray application using drone sprayer. Commercial drone manufacturers are adopting drones without having basic information on the performance and efficacy of the drone spraying system in terms height of spray, nozzle flow rate, operating pressure, type of nozzle and nozzle configuration, spray uniformity and application rate. The present investigation was taken up to study and optimize spray operational parameters of drone sprayer under laboratory condition.

2 Materials and methods 2.1 Drone The drone sprayer used in the present investigation, was an E610P six-rotor electric (M/s. EFT Electronic Technology Co., Ltd., Hefei City, China) is shown in Figure 1 and specifications are presented in Table 1. The spraying system of the drone sprayer mainly consisted of Flight controller (1), Brushless direct current (BLDC) motors arm (2), Fluid hose pipe (3), BLDC motor (4), Support frame (5), Pesticide tank (6), Landing gear (7), Foldable propeller (8), Lithium polymer (LiPo) batteries (9). The UAV sprayer has two LiPo batteries of 6 cells each with a capacity of 16,000 mAh to supply the necessary current required for the propulsion system. A 24 V BLDC motor coupled with a pump was used to pressurize the spray liquid and then atomize it into fine spray droplets. This drone spray model has the functions of GPS route planning and breakpoint return, which could complete aerial spraying operations autonomously.

2.2 Study the machine and operational parameters of drone sprayer The selected autonomous battery-operated drone sprayer (Make: EFT Electronic Technology, Model: E610P) was tested and calibrated in the laboratory condition Agricultural Machinery Research Centre (AMRC), Department of Farm Machinery and Power Engineering, Agricultural Engineering College and Research Institute Agricultural University, Coimbatore (11.0122° N, 76.9354° E) by taking different variables which mainly influence the functional performance. ASAE (S341.5) standard calibration procedure has been followed to assess the different spray operational parameters (19).

2.2.1 Measurement of nozzle discharge rate, spray operating pressure and spray angle A handheld portable digital nozzle tester (AAMS, Maldegem, Belgium) and digital liquid pressure gauge instrument (Make:

FIGURE 1

Electric battery-operated drone sprayer.

diaphragm pump in terms of Pulse Width Modulation (PWM) ranging from 0 to 100% as shown in Figure 2.

TABLE 1 Specifications of drone sprayer.

Main parameter Type

Norms and numerical values

2.2.2 Experimental setup

Hexacopter

Item Model

The diaphragm pump inlet is connected to the fluid tank and its outlet is connected to the main line of four nozzles (2020A-132 series, M/s Ningbo Licheng Agricultural Spray Technology Co., Ltd., Zhejiang, China). Digital liquid pressure gauge and spray flow sensor (Make: Sea, Model: T1A/K3A) were connected in between diaphragm pump outlet and nozzles main hose pipe and pressure was recorded in terms of kg cm−2. An experiment was conducted to assess the effect of drone sprayer BLDC spray motor speed on pump operating pressure, nozzle discharge rate and spray angle. The experimental layout in Agricultural Machinery Research Centre (AMRC), Department of Farm Machinery and Power Engineering, Agricultural Engineering College and Research Institute, Agricultural University, Coimbatore (11.0122° N, 76.9354° E) and is shown in Figure 3. Initially, transmitter sends the PWM percentage signals (1) to flight controller through receiver. Then spray water flows from fluid tank (2) to spray diaphragm pump (3). The rotational speed of BLDC motor was recorded as a PWM percentage and then converted it in to revolutions per minute using a contactless digital tachometer (Make: Kusam Meco, Model: Km-2234Bl) (4). The operating pressure of spray fluid was recorded using digital liquid pressure gauge instrument (5) and provides the live water flow rate feedback information from water flow sensor (6). Then, recorded the pump flow rate of nozzle (7) in terms of liter per min at 0, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100% of PWM using a handheld portable nozzle tester (8). Simultaneously, captured the images of each nozzle spray and calculated the actual spray angle using a digital protractor (Make: Yuzuki, Model: IP65). The experimental setup and arrangement for measurement of spray liquid discharge rate, spray motor speed and spray angle are shown in Figures 4–6, respectively.

E610P

Unfold fuselage size, (L × W × H), mm

2000 × 1800 × 670

Folding Size, (L × W × H), mm

950 × 850 × 670

Power source

12S 16,0000 mAh LiPo Battery

Payload capacity, L

10

Self-weight, kg

6.9

Take-off weight, kg

26

Flight height, m

1–20

Forward travel speed, ms−1

0–8

Type of spray nozzle

Flat fan shape

Number of nozzles

4

Discharge rate, l m−1

0–3.2

Swath width of spray, m

3–5

Liquid pressure, kg cm

3.4

Remote controller distance, km

1.5

No-load flight time, min

25

Charging time, min

90

−2

Shanghai XuYan Precision Technology Co., Ltd., Model: XY-PG560R) were used to measure spray liquid discharge rate and operating pressure at specific time interval while operating the drone sprayer under normal conditions. A24 V DC brushless direct current (BLDC) motor and diaphragm pump were used to pressurize the spray fluid. This BLDC motor is connected to power distribution board and signal wires were connected to motor port in flight controller (Make: JIYI, Model: K++ V2, Version: V1.5.1). This autonomous drone sprayer has inbuilt intelligent/ precise spray discharge rate control system at different rotation of BLDC motor speed with PWM from Agri Assistant mobile app (Version: V1.5.1). The Agri Assistant App has a display showing the flow rate of

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2.3 Development of spray patternator A spray patternator of 5.0 m x 5. 0 m was developed as per the BIS standard (IS: 10064–1982) to study and optimize the spray operational

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FIGURE 2

Screen display view of intelligent/precise spray liquid flow control system in terms of PWM (%).

parameters of the drone sprayer viz., height of spray, operating pressure and nozzle mounting configuration under laboratory condition (21). The patternator was fabricated using M.S. channel for the frame and sheet (Figure 7). The spray patternator surface was composed of 0.2 cm thick M.S. sheet positioned horizontally over the frame. The patternator has 91 continuous V- type channels at equal spacing mounted on the rectangular frame. According to IS: 8548 and IS 10064 standards, channels should have 25 ± 0.25 mm width and 100 mm depth (20, 21). These constraints make patternator difficult and costly to develop. Bended M.S. sheet in V shape channels with 55 mm width is more than the recommended width to eliminate splash-back between the measurement grooves due to high downwash airflow produced by the rotor propellers of the drone sprayer. The rectangular frame on which sheets were placed, was made up of 5 mm × 5 mm L-shaped MS channel. Measuring cylinders of 190 mL capacity were placed below each channel to collect the spray liquid. The arrangement of measuring jars and funnel in spray patternator is shown in Figures 8, 9 respectively. Patternator has 25° slope for easy movement of water to the jar. The developed spray patternator is shown in Figure 10. The specifications are mentioned in Table 2.

distribution system. In the hexa standard type nozzle configuration (Figure 11), four nozzles were mounted below the rotors of the drone sprayer as per the motor BLDC motor configuration and another set of four numbers of flat fan nozzles were placed on the boom type nozzle configuration at equal interval distance (Figure 12). The nozzle spacing of boom type nozzle configuration was optimized at three operating pressures (3.0, 4.0 and 5.0 kg cm−2) and three nozzles spacing (0.30, 0.45 and 0.60 m). The height of spray 0.545 m is the distance between the tip of the nozzle to the top of patternator V channel surface was selected as per the recommendation IS: 3652 for flat fan nozzle. A Light Detection and Ranging (LIDAR) distance meter instrument

(M/s, DEKOPRO, LRE520 80 M) was used to adjust the height of spray. The spray liquid was horizontally directed and landed on the equidistance V shaped channels. When the fluid reaches the patternator surface, it will be collected in different channels. Each channel is provided with own graduated cylinder at the base of the patternator. The spray liquid in the graduated cylinder of the patternator was collected and the quantity of liquid from each channel was measured and noted. The layout of boom and standard hexa type nozzle configuration with patternator is shown in Figures 13, 14 respectively.

2.4 Optimization the nozzle spacing and operating pressure for boom and hexa nozzle configuration attachment drone

2.4.2 Analysis of spray distribution system The coefficient of uniformity and spray width were the two main parameters for optimizing the nozzle spacing and operating pressure. These parameters directly influence work efficiency and spray quality.

The experiment was conducted for spray volumetric distribution patterns using a specially designed and fabricated spray patternator at the Agricultural Machinery Research Centre (AMRC), Department of Farm Machinery and Power Engineering, Agricultural Engineering College and Research Institute, Tamil Nadu Agricultural University, Coimbatore (11.0122° N, 76.9354° E). The Drone sprayer volume distribution test was conducted as per the IS: 8548 and IS: 10064 and ASAE (S386.2) standards (20–22).

2.4.3 Liquid distribution uniformity coefficient The liquid distribution uniformity coefficient (CV) compiles all the patternator data points and summarizes them into a simple percentage, indicating the amount of variation within a given distribution. The uniformity coefficient (CV) (Equations 1–3) is commonly used to quantify the uniformity of spray systems; higher CV values indicate poor uniformity in the spray pattern and the uniformity coefficient is calculated according to the following equation (12, 13):

2.4.1 Experimental setup Two types of nozzles mounting configuration viz., boom and hexa standard type were used in drone sprayer to understand the spray volume

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FIGURE 3

Experimental layout for measurement of spray motor speed, sprayer discharge rate, operating pressure and spray nozzle angle.

CoefficientofVariation (CV) =

Mean (X) =

Standarddeviation (SD) =

SD x 100 X

the effective application rate. The effective spray width was determined in a manner that will give the most uniform overall application rate.

(1)

∑ Xi N

(2)

N

∑1 (X i − X) N −1

2.5 Test of spray volume distribution pattern in hover outdoor condition

2

Uniformity coefficient was selected to study and optimized nozzle spacing and operating pressure of operational parameters boom and standard hexa nozzle configuration attachment to drone sprayer in outdoor condition.

(3)

Where, CV – Liquid distribution uniformity coefficient. X – Volume of liquid contained in specific container, ml. Xi – Average volume of liquid, ml. N – Number of analysed containers. Spray distribution uniformity can be obtained with a low coefficient of variation. The above procedure was followed throughout this investigation to determine the coefficient of variation of spray uniformity distribution of the drone sprayer with boom arrangement.

2.5.1 Experimental setup Four flat fan nozzles were mounted on the boom with optimized nozzle spacing (0.60 m) and attached below the drone sprayer fluid tank and landing gear structure. The arrangement of optimized nozzle spacing on the spray boom and attachment to drone sprayer is shown in Figures 15, 16. Another set of four nozzles were mounted below the BLDC rotors as a hexa standard nozzle configuration attachment and is shown in Figures 17, 18. To record and analyse the spray volume distribution pattern for boom and hexa standard nozzle configuration, the drone sprayer hovered at three flight heights viz., 1.0 m, 2.0 m, and 3.0 m. These are the independent variables that mainly influence the functional

2.4.4 Effective spray width The effective spray width is the distance between the points on either side of a single swath where the deposit rate equals one-half of

FIGURE 4

Experimental layout for measurement of spray discharge rate using nozzle tester.

FIGURE 7

Isometric view of spray patternator.

FIGURE 5

Experimental layout for measurement of spray motor speed.

FIGURE 8

Arrangement of measuring jar in spray patternator.

FIGURE 6 FIGURE 9

Experimental layout for measurement of spray angle.

Arrangement of funnel in spray patternator.

performance of the drone spray volume distribution pattern in terms of quantity of spray volume collected (ml), coefficient of uniformity (%) and spray width (mm). For each treatment, a 10 litre water tank was filled and the spray volume was measured in each measuring jar. Each treatment was carried out three times. The coefficient of uniformity and spray width were calculated for three spray hover

heights. This spray volume distribution pattern test procedure was followed as per IS: 8548 and ASAE (S386.2) standards (20, 22). Figure 19 and Supplementary Figures S1, S2 show the volumetric distribution of the drone sprayer with boom and hexa standard nozzle configuration in the patternator and the volume of liquid collected in the measuring jar.

FIGURE 10
Developed spray patternator for spray volume distribution measurement.

TABLE 2 Speciation of developed spray patternator.

Main parameter	Norms and numerical value
Overall Size, (L × W × H), mm	5,000 × 5,000 × 600
Support frame structure	L-shaped M.S. channel
Sheet material	V channel
Size (L x W), mm	2,500 × 1,250
Material	M.S sheet
Number of sheets	12
Numbers	91
Width, mm	55
Depth, mm	35
Patternator inclined slope, degree	25
Number of measuring cylinders	91

FIGURE 11
Hexa standard type spray nozzle arrangement.

2.6 Statistical analysis

meteorological parameters viz., air temperature, wind velocity, humidity and rainfall were recorded during at outdoor condition. A portable anemometer was mounted on a square iron pipe (20 x 20 x 2 mm) at 2.0 m above the ground level to measure the wind velocity. Weather conditions, including wind speed, air temperature, and relative humidity during the study, are presented in Table 3.

A study included two independent variables: (1) nozzle spacing (i.e., 300, 450 and 600 mm), (2) operating pressure (i.e., 3, 4 and 5 kg cm−2), and two dependent variables (i.e., uniformity distribution and spray width) with three replications. The factorial CRD design for the analysis of variance (Two-way ANOVA) tests to determine if there are significant differences between the spraying nozzle spacing and operating pressure. All tests were replicated thrice and the statistical analysis was carried out in OPSTAT Software (O. P. Sheoran, a computer programmer at CCS HAU, Hisar, India) to determine the level of significance.

3 Results and discussion 3.1 Results of drone spray operational parameters

2.7 Recording of meteorological parameters during outdoor condition test

The spray operational parameters such as operating pressure, nozzle discharge rate and spray angle were measured using standard procedure. The mean value of total spray discharge rate, spray angle and operating pressure of combined four nozzles at different motor speed mode of 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100% of PWM is furnished in Table 4.

During the drone spray volume distribution pattern test for optimizing the height of spray and nozzle configuration, the different

From Table 4, it was observed that the spray discharge rate and spray angle increased with the increase in spray operating pressure. Spray angle was measured using digital protractor and shown in Supplementary Figure S3. Among the 10 different modes of spray motor speed, 50, 70 and 100% modes were selected as it produced discharge rate 2.8 L m−1, 3.1 L m−1and 3.4 lm−1 at 3 kg cm−2, 4 kg cm−2and 5 kg cm−2, respectively for the investigation on the spray volume distribution pattern of boom and hexa standard nozzles experiment in hover condition.

3.2 Results of spray volume distribution pattern for single nozzle FIGURE 12

The volume discharge rate of single nozzle was tested at a different pressure level of 3.0, 4.0 and 5.0 kg cm−2 on the patternator in the

Boom type spray nozzle arrangement.

FIGURE 13

Experimental layout for mounting of spray boom type nozzles arrangement on spray patternator.

FIGURE 14

Mounting of nozzle in hexa standard arrangement on spray patternator.

FIGURE 15

Top view of mounting of spray boom type nozzle arrangement to drone sprayer.

FIGURE 16

Arrangement of spray nozzles on boom configuration and attachment to Drone sprayer.

3.3 Effect of nozzle spacing and operating pressure on spray uniformity

laboratory prior to the outdoor test trials. Spray pattern at 4.0 kg cm−2 pressure was found to have uniform distribution pattern based on the CV. The spray pattern of a single flat fan nozzle at different operating pressures are shown in Supplementary Figure S4. The volume of liquid collected from each container in respect to the total volume of liquid collected from all the containers and the coefficient of variation was calculated for different pressures. The standard bell curve was observed at all the nozzle pressures. Based on coefficient of variation (53.0%), the spray volume distribution pattern was found to be high at 4.0 kg cm−2 nozzle pressure. From the laboratory test, an optimized nozzle pressure of 4.0 kg cm−2 was maintained to test the drone spray with different nozzle arrangements at outdoor condition.

The effect of nozzle configuration, operating pressure and nozzle spacing on spray uniformity distribution and spray width was analyzed. The spray distribution pattern test for optimization of nozzle spacing and operating pressure for both boom type and hexa standard nozzle configuration based on coefficient of variation is presented in Table 5 and Supplementary Figure S5. The minimum coefficient of variation (CV) represents the better spray uniformity distribution Luck et al. (12) and Padhee et al. (13).

FIGURE 17

Schematic diagram of nozzles arrangement in hexa standard configuration attachment to drone sprayer for outdoor test.

FIGURE 18

Top view of mounting of hexa standard arrangement type nozzle arrangement to drone sprayer.

From Table 5 and Supplementary Figure S5, for boom spray arrangement, the maximum coefficient variance (CV) value was found to be 52.08% at 3 kg cm−2 operating pressure and 300 mm nozzle spacing. The minimum CV value was found to be 36.99% at pressure of 4.0 kg cm−2 and 600 mm nozzle spacing. Luck et al. (12) and Padhee et al. (13) presented spray liquid uniformity distribution was better with lower CV value. Hence on the spray uniformity distribution results in Table 5, the optimized nozzle spacing of 600 mm and a 4.0 kg cm−2 operating pressure were selected with lower CV value

36.99% for boom spray arrangement on the drone sprayer for hover condition test. The maximum spray width value was found to be 3,235 mm at 4 kg cm−2 operating pressure and 600 mm nozzle spacing. The minimum spray width value was found to be 2,035 mm at pressure of 3.0 kg cm−2 and 300 mm nozzle spacing. In the hexa standard type nozzle configuration, four nozzles were mounted below the rotors of the drone sprayer. The spray distribution pattern test for optimization of operating pressure for hexa standard nozzle configuration based on coefficient of variation is presented in

FIGURE 19

Schematic diagram of nozzles arrangement in boom configuration attachment to drone sprayer for outdoor test.

TABLE 3 Meteorological data during the spray volume distribution pattern test.

TABLE 4 Results of spray motor speed, pressure, nozzle flow rate and nozzle spray angle.

Environmental parameters	Values
Air temperature, °C	28.3 to 30.9
Relative humidity, %	54.5 to 60.2
Motor speed mode (%)	
Wind velocity, ms−1	

0.11 to 0.21

10

0

Rainfall, mm

Table 5. From Table 5 and Supplementary Figure S6, for hexa standard nozzle arrangement, the maximum CV value was found to be 50.57% at 5 kg cm−2 operating pressure. The minimum CV value was found to be 48.31% at pressure of 4.0 kg cm−2. Based on the spray uniformity distribution value, the optimized 4.0 kg cm−2 operating pressure was selected for hexa standard spray arrangement on the drone sprayer for hover condition test. Supplementary Table S1 presents the statistical analysis, i.e., analysis of variance showing the p-value for dependent variable at 5% significance level. A p-value above 0.05 was observed for uniformity of distribution and spray width. Therefore, the nozzle spacing had a significant effect on uniformity distribution and spray width. Operating pressure shows not significant in uniformity distribution and significant in spray width. There is significant interaction effect between nozzle spacing and operating pressure for spray width.

Pressure (kg cm−2)

Discharge rate (lm−1)

Spray angle (degree)

247.0

0.2

1.0

66.52

20

606.0

0.3

1.5

71.25

30

1192.3

0.6

1.8

75.92

40

1730.3

1.5

2.1

86.87

50

2197.7

3.0

2.8

92.67

60

2781.0

3.7

3.0

97.07

70

3394.7

4.0

3.2

99.32

80

4017.3

4.3

3.3

101.25

90

4491.0

4.6

3.3

103.37

100

4514.0

5.0

3.4

105.17

below the rotors of the drone sprayer operated at 4.0 kg cm−2 operating pressure. The drone sprayer with boom spray nozzle configuration hovered at three heights of spray viz., 1.0, 2.0 and 3.0 m and spray volume were collected from each jar during outdoor conditions (average wind speed, air temperature and relative humidity were measured as 0.19 m s−1, 28.3°C and 57%, respectively). The effects of nozzle configuration and hover height on spray uniformity distribution, spray width and total quantity of liquid collected were analyzed in single pass distribution method and presented in Supplementary Table S2.

3.4 Spray volume distribution pattern of drone sprayer in hover at outdoor condition

3.4.1 Effect of nozzle configuration and height of spray on spray uniformity

The spray volume distribution pattern test was conducted and analyzed to optimize the height of spray based on coefficient of variation at outdoor condition. For boom type nozzle configuration, four numbers of flat fan nozzles were placed with 0.60 m spacing and in the hexa standard nozzle configuration, four nozzles were mounted

According to the coefficient of variation results presented in Supplementary Table S2, the spray height has a significant impact on spray uniformity distribution. Lower spray uniformity distribution

TABLE 5 Results on effect of type of nozzle configuration, nozzle spacing and operating pressure on uniformity of distribution and spray width.

Type of Nozzle configuration

Nozzle spacing (mm)

Operating pressure (kg cm−2)

Uniformity of distribution, CV (%)

Spray width (mm)

300

3

52.08

2034

4

55.80

2,145

5

54.29

2,145

3

45.72

2,530

4

44.61

2,640

5

44.21

2,640

3

37.63

3,025

4

36.99

3,235

5

38.35

3,235

3

49.36

2,530

4

48.31

2,695

5

50.57

2,751

450 Boom

600

35/70 Hexa

(57.21%) was found at 1.0 m height of spray for hexa standard nozzle configuration. Similarly, the maximum spray uniformity distribution was found as 47.26% at 2.0 m height of spray. It was also observed that when the drone sprayer hover height was increased from 1.0 m to 2.0 m from the top of the patternator, better spray uniformity distribution was recorded. When the height was increased from 2.0 m to 3.0 m from the top of the patternator, the volume of liquid collected and uniformity of distribution from the target area was reduced, which may be due to side drift. In boom nozzle configuration, lower spray uniformity distribution of 58.42% was found at 1.0 m hover height. Similarly, the maximum spray uniformity distribution of 54.80% was observed at 2.0 m hover height. It was also observed that when the drone sprayer hover height was increased from 1.0 m to 2.0 m from the top of the patternator, better spray uniformity distribution was found for both nozzle configuration.

N3 to N4 were measured as 35 cm, whereas the distance between the nozzles N2 to N3 was measured as 70 cm. The spray volume was collected at three hover heights, viz., 1,000, 2,000 and 3,000 mm from the top of the patternator surface and results are presented in Supplementary Table S1 and Supplementary Figure S7. When compared to the height of spray, the volume of water collected at the central portion of the drone sprayer was less (5,389 mL) when hovered at 1.0 m height compared to 2.0 m (5,949 mL) and 3.0 m (5,559 mL) heights. From the Supplementary Table S2 and Supplementary Figure S8 for boom nozzle configuration, it was found that, due to downwash air flow and increase in horizontal distance between the nozzles N2 and N3, the volume of liquid collected below the drone was less, irrespective of the height of operation of the drone above the patternator, it was also observed that more round vertex patterns were generated at 1.0 m hover height compared to the hover height of 2.0 and 3.0 m due to the direct impact of downwash airflow generated by the rotor propellers on the droplets. At 1.0 m hover height, most of the spray droplets were distributed back to the upper side and did not move towards the downside V-channel surface of the patternator. The liquid collected at the center of drone sprayer was less (5,190 mL) at 1.0 m hover height, whereas it was 6,230 mL and 5,146 mL at 2.0 m and 3.0 m hover heights, respectively. Supplementary Table S3 presents the statistical analysis, i.e., analysis of variance showing the p-value for dependent variable at 5% significance level. Therefore, the nozzle configuration, height of spray had a significant effect on uniformity distribution, spray width and quantity of liquid collected. There is significant interaction effect between nozzle configuration and height of spray for uniformity of distribution, spray width and quantity of liquid collected.

3.4.2 Effect of nozzle configuration and height of spray on spray width From Supplementary Table S2, the spray width of hexa standard nozzle arrangement was found to be minimum, (3,145 mm) for 1.0 m hover height, whereas it was found to be maximum, (3,865 mm) at 2.0 m hover height. In boom nozzle configuration, the minimum spray width was found as 4,450 mm for boom nozzle arrangement at 1.0 m height, which was higher (3,145 mm) than the hexa standard nozzle arrangement at the same hover height. The maximum spray width was found as 4,902 mm at 2.0 m height of boom spray. It was observed that the spray width increased by increasing the height of spray from 1.0 to 2.0 m from the patternator. The height of spray did not influence the discharge rate during the laboratory trials. Generally, it was observed that the spray width of boom nozzle arrangement is higher than the hexa standard nozzle arrangement.

3.4.3 Effect of hover height on quantity of liquid collected

3.5 Spray volume distribution pattern test in one direction application method

In hexa standard nozzle configuration, four numbers flat fan nozzles viz., N1, N2, N3 and N4 are mounted below the rotor propeller. The horizontal distance between the nozzles N1 to N2 and

In one direction application method, the overlaps between two passes were considered. The spray uniformity and effective spray

width were calculated and the results are presented in Supplementary Table S4. According to the coefficient of variation results in Supplementary Table S4 and Supplementary Figures S9, S10, spray height has a significant impact on spray uniformity distribution. Lower spray uniformity distribution with maximum CV was found as 19.83 and 21.62% and at 1.0 m height of spray for boom and hexa standard nozzle configuration. Similarly, the maximum spray uniformity distribution with minimum CV was found as 18.90 and 17.95% at 2.0 m height of spray boom and hexa standard nozzle configuration. It was also observed that when the drone sprayer hover height was increased from 1.0 m to 2.0 m from the top of the patternator, better spray uniformity distribution was found. Similarly, the minimum spray width was found to be 2,805 mm and 2,035 mm at 1.0 m height of spray for boom and hexa standard nozzle arrangement, respectively. The maximum spray width was found to be 3,190 mm and 2,310 mm at 2.0 m height of spray for boom and hexa standard nozzle arrangement, respectively. It was observed that the spray width was increased by increasing the height of spray from 1.0 m to 2.0 m from the patternator. The effective spray width in one direction spray distribution for boom nozzle configuration at 1.0, 2.0 and 3.0 m height of spray is shown in Supplementary Figure S10. Similarly, for hexa standard nozzle configuration, the spray distribution pattern is given in Supplementary Figure S9. Supplementary Table S5 presents the statistical analysis, i.e., analysis of variance showing the p-value for dependent variable at 5% significance level. A p-value above 0.05 was observed for uniformity of distribution for nozzle configuration. Therefore, the height of spray had a significant effect on uniformity distribution and spray width. There is significant interaction effect between nozzle configuration and height of spray for uniformity of distribution and spray width. In boom nozzle arrangement (Supplementary Figure S9), it was also observed that more round vertex patterns were generated during the 1.0 m and 3.0 m hover height compared to the 2.0 m hover height due to the direct impact of downwash airflow generated by the rotors. At 1.0 m hover height, most of the spray droplets were distributed back to the upper side and did not move towards the downside V-channel surface of the patternator. In hexa standard nozzle arrangement (Supplementary Figure S10), it was also observed that there was less round vertex pattern generated during hexa configuration nozzle spray compared to boom type nozzles due to the direct impact of downwash airflow generated by the rotor propeller. The downwash airflow produced by the rotor propellers reduced the liquid distribution uniformity coefficient and significantly influenced the change of the lateral distribution pattern of spray drops produced by the flat fan spray nozzles. Similarly, as in previous research works Berner and Chojnacki (14) and Qing et al. (15) there was a change in the shape of liquid deposition on the patternator due to the influence of downwash airflow produced by the drone rotor propellers. Similarly, as in previous research works Yallappa et al. (11) and Pachuta et al. (16) the asymmetry of the airflow distribution generated by the drone rotors with respect to the nozzle axis is what causes the lateral spray liquid distribution of the settled liquid on the patternator to change shape. The volume of the liquid that was deposited in the patternator later grooves also varied significantly Chojnacki and Pachuta (17). A higher spray distribution amount of the liquid was sprayed from the twin flat nozzle than from the single flat nozzle (18).

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Earlier reported work was done at a constant spray height, where in the present investigation, the results were obtained at varying sprays heights (1.0, 2.0 and 3.0 m) and nozzle spacing (30, 45, 60 cm) at an optimized operating pressure (5.0 kg cm−2). The results showed that there were obvious differences in the distribution of spray volume patterns for boom and hexa configuration nozzles.

4 Conclusion Food and nutritional security is the situation where in public around the globe, in all conditions must maintain constant physical and financial, ensuring reliable global access to sufficient nutritious and safe food. Results of in this experiment are study and optimized the spray operational parameters viz., height of spray, nozzle spacing and spray operating pressure. Nozzle spacing and operating pressure for boom and hexa standard nozzle configuration to drone sprayer was optimized by using developed spray patternator (5.0×5.0 meter). The optimized nozzle spacing of 0.6 m and a 4.0 kg cm−2 operating pressure was chosen for the drone

sprayer distribution test at outdoor conditions based on the spray uniformity distribution value. The spray volume distribution for both boom and hexa standard nozzle arrangement in hover condition, observed that when the drone sprayer hover height was increased from 1.0 m to 2.0 m from the top of the patternator, better spray uniformity distribution, spray width and quantity of liquid collected was recorded. The central portion of the patternator collected less water (5,194 mL) when a drone sprayer hovered at 1.0 m height compared to 2.0 (5,416 mL) and 3.0 m (6,231 mL) hover heights. With the increase of hover height, the change of the downwash airflow led to a gradual decrease in spray volume distribution in the effective spray area. A better spray uniformity distribution was found when the drone sprayer hover height was increased from the top of the patternator. A more round spray droplet vertex pattern was generated during the 1.0 m hover height compared to the 2.0 and 3.0 m hover heights due to the direct impact of downwash airflow generated by the rotors. Downwash airflow produced by rotor propellers reduced the liquid distribution uniformity coefficient and significantly influenced the change of lateral distribution pattern of spray drops produced by the flat fan spray nozzles. Thus, the drone sprayer should be operated at an appropriate spray height of 2.0 m to attain the recommended application rate of pesticides. The good spray uniform distribution was found in hexa configuration nozzle arrangement as compared to the boom arrangement of nozzles. The study provides references for the height of spray and different nozzle configuration arrangement to drone sprayer for efficient operation. Lastly, the study demonstrates that optimizing drone sprayer parameters, such as spray height and nozzle configuration, ensures efficient pesticide application, leading to enhanced food and nutritional security by promoting sustainable agricultural practices under varying climate conditions.

Data availability statement The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

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Author contributions

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DY: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Investigation, Supervision, Validation. RK: Funding acquisition, Project administration, Resources, Validation, Visualization, Writing – review & editing. AS: Conceptualization, Data curation, Formal analysis, Resources, Validation, Visualization, Writing – review & editing. BS: Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – review & editing. AM: Conceptualization, Data curation, Formal analysis, Supervision, Writing – review & editing. BK: Writing – original draft, Writing – review & editing, Software, Formal analysis, Data curation, Investigation. MK: Writing – original draft, Writing – review & editing, Project administration, Supervision, Investigation, Resources.

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A review on drones controlled in real-time Vemema Kangunde1

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Abstract This paper presents related literature review on drones or unmanned aerial vehicles that are controlled in real-time. Systems in real-time control create more deterministic response such that tasks are guaranteed to be completed within a specified time. This system characteristic is very much desirable for drones that are now required to perform more sophisticated tasks. The reviewed materials presented were chosen to highlight drones that are controlled in real time, and to include technologies used in different applications of drones. Progress has been made in the development of highly maneuverable drones for applications such as monitoring, aerial mapping, military combat, agriculture, etc. The control of such highly maneuverable vehicles presents challenges such as real-time response, workload management, and complex control. This paper endeavours to discuss real-time aspects of drones control as well as possible implementation of real-time flight control system to enhance drones performance.

Keywords Drones · Unmanned areal vehicles · Real-time control · Real-time operating system · Global positioning system · Inertial measurement unit

1 Introduction A drone, also known as unmanned aerial vehicle (UAV), is an aircraft without a human pilot on board [1,2]. There has been a rapid development of drones for the past few decades due to the advancement of components such as micro electro-mechanical systems (MEMS) sensors, microprocessors, high energy lithium polymer (LiPo) batteries, as well as more efficient and compact actuators [3–5]. Drones are now present in many daily life activities [2,6–8]. They are used in many applications such as inspecting pipelines and power lines, surveillance and mapping, military combat, agriculture, delivery of medicines in remote areas, aerial mapping, and many others [2,9–12]. See Figs. 1 and 2 for some drones applications. Robotic manipulators, found in many applications [13–15], have in recent years been implemented on UAV platforms [16–18] for tasks such as aerial manipulation, grasping, and cooperative transportation. The unstable dynamics of the robotic arm, which increase control complexity of UAVs, have widely been studied in the literature [19–22].

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UAVs technology is rapidly growing while UAV solutions are being proposed at faster rates as various needs arise. Drone features are determined by specific UAV applications as well as competition in the commercial market [23,23–25]. In [26], a review of the most recent applications of UAVs in the cryosphere was conducted. Compared to conventional spaceborne or airborne remote sensing platforms [27–29], UAVs offer more advantages in terms of data acquisition windows, revisits, sensor types, viewing angles, flying altitudes, and overlap dimensions [26,30–32]. The review shows that across the world, applications used various multirotor and fixed-wing UAV platforms. Red, green, blue (RGB) sensors were the most used, and applications utilised quality video transmission to the ground control station. The study in [33] demonstrates how versatile and fast-growing is the adoption of UAV solutions in daily life scenarios. They propose the design of a system capable of detecting coronavirus automatically from the thermal image quickly and with less human interactions using IoT-based drone technology. The UAV system is equipped with two cameras: an optical camera and a thermal camera. It conveys to the ground control station (GCS) the image of the person, the global positioning system (GPS) location as well as a thermal image of the hot body detected. The system combines IoT, virtual reality, and live video feedback to control the camera for monitoring people.

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Fig. 1 The KC2800 is a fixed-wing drone used for surveillance and mapping. Picture reprinted from https://aibirduav.diytrade.com

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On the other hand, apart from advancements in custommade drones, commercial drone manufacturers are actively improving their products. Latest, more advanced drones are presented at https://thewiredshopper.com, see Figs. 3 and 4. DJI Phantom 4, for example, is equipped with an automatic collision avoidance system. It has a sport mode that disables collision detection and enables fast speeds. It also has an active tracking technology that enables the selection of another moving object, like a car or another drone, and the Phantom 4 will autonomously follow it without assistance from the human pilot. The drone is equipped with a 3-axis camera and can record 4K resolution video at 30 fps and 1080p resolution at 12 fps. It will take 12-megapixel images in Adobe DNG raw format. It has gimbal stabilization technology and a built-in video editor. Other latest drones in the market include the AirDog drone by AirDog, 3DR Solo Drone by 3DRobotics, and Yuneec Typhoon H by Yuneec. A UAV's operational environment is highly dynamic due to unpredictable changes in weather conditions affecting the air space. For drones to be reliable, their flight controllers must adapt to these environmental changes in real-time. Control of highly maneuverable UAVs has been extensively studied for the past decades.

2 Drone hardware overview Fig. 2 Quadrotor drone spraying pesticide on crops. Picture reprinted from https://www.indiamart.com

Fig. 3 Phantom 4. Picture reprinted from https://thewiredshopper.com

Fig. 4 3DR Solo. Picture reprinted from https://thewiredshopper.com

A UAV is controlled by an embedded computer called the Flight Control System (FCS) or flight controller [34–36], basically consisting of a control software loaded into a microcontroller. The microcontroller reads information from on-board sensors, such as accelerometers, gyroscopes, magnetometers, pressure sensors, GPS, etc.,as well as input from the pilot, perform control calculations, and control the motors on the UAV [37,38]. The FCS as well as the set of sensors would be mounted on the drone air frame. Drone air frames, typically made of strong, light composite materials, are mostly relatively small with limited space for avionics [39,40]. A set of sensors, such as TV cameras, infrared cameras, thermal sensors, chemical, biological sensors, meteorological sensors etc., used to gather information during drone applications need to be lightweight to reduce UAV payload [41–44]. The information gathered from the sensors can be partially processed on-board or

transmitted to the ground station for further processing [45–47]. An onboard controller, separate from the flight controller, can be used to operate the payload sensors [48–50]. Figure 5 shows the Cc3d open source flight controller used as a UAV flight controller. The Pixhawk flight controller is an open-source hardware project equipped with sensors necessary for flight control [51–53]. It includes a CPU with RAM as well as gyroscope, compass, 3-axis accelerometer, barometric pressure,

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Fig. 5 UAV hardware components. Picture reprinted from https://www. google.com/search?q=Cc3d+ +flight+controller

and magnetometer [54,55]. The Paparazzi flight controller, developed by Ecole Nationale de lAviation Civil (ENAC) UAV Lab since 2003 [34], is the first and oldest open-source drone hardware and software project. In March 2017 ENAC Lab released the Paparazzi Chimera autopilot. A detailed survey on open-source flight controllers was disclosed by Ebeid et.al in [34]. An autopilot software is used for drone automatic flight control [56]. On the other hand, drones can be operated remotely through a remote controller [57–59].

2.1 State observation The FCS requires information on UAV states such as attitude, position, and velocity for control implementation [60]. The commonly used state observer is the inertial guidance system. Other attitude determination devices such as infrared or vision based sensors can be used [61,62]. The inertial guidance system (IGS), also referred to as inertial navigation system (INS) [63] consists of the inertial measurement unit (IMU) and the navigation computer. The IMU has three orthogonal rate-gyroscopes, three orthogonal accelerometers and sometimes 3-axis magnetometer to determine angular velocity, linear acceleration and orientation respectively [64]. Inertial guidance systems are entirely self reliant within a vehicle where they are used. They do not rely on transmission of signals from the vehicle or reception of signals from external sources. Inertial guidance systems can be used to estimate the location of the UAV relative to its initial position using a method known as dead reckoning [65]. Global navigation satellite system (GNSS) provides location estimates using at least four satellites [65].

2.2 State estimation State estimation feedback is required for UAV control, such estimates are usually for attitude, position, and velocity [66]. On board sensor readings are fed to the UAV autopilot system to generate UAV state estimates [67]. The need for state estimation is due to the fact that data from measurement sensors

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is prone to uncertainties due to atmospheric disturbances, vibrations noise, inaccuracy of coordinate transformations, and missing measurements [68]. Sensors such as the GPS suffers from signal obstruction and reflections caused by nearby objects leading to missing or inadequate information [69]. To compensate for uncertainties and lack of information from individual sensors, multiple sensor data fusion can be employed to incorporate advantages of different types of sensors [70]. The altitude heading and reference system combines gyroscope, accelerometer, magnetometer, GPS and pressure sensors to measure UAV states. Sensor data for state estimates need to be updated at a relatively high frequency, normally above 20 Hz for small UAVs. Kalman filtering can be employed to make optimal estimations for sensors with lower update frequencies, such as the GPS, which typically has an update frequency of 4 Hz. Kalman filtering can also be used to process gyroscope readings which are susceptible to noise and drift. The other technique to improve gyroscopic readings is to model the gyroscope random noise and then offsetting it according to the model, this is referred to as model compensation [71].

2.3 Controller design for autopilots Most current commercial and research autopilots focus on GPS-based waypoints navigation to follow a desires path [72]. Waypoint navigation is essential for autonomous control of UAVs for UAV tasks beyond the pilot's sight. The pilot could control the UAV from the GCS using a graphical User Interface (GUI), the location as well as other needed information about the UAV would be displayed at the the GCS [45]. The path following control of a UAV involves the control of roll, pitch, altitude and air speed for trajectory tracking and waypoint navigation [73]. GPS waypoint navigation involves providing sequential GPS coordinates that contains locations and heights of the UAV flight [72]. The set of pr-programmed GPS waypoints then becomes the path for the UAV to follow [74]. In

2.4 Microcontrollers used An FCS has sensor packages for state determination, onboard processors for control and estimation uses, and peripherals for communication links and data transfer. For small UAV applications , small, light weight, and often low power consumption hardware components for the FCS are preferable. Successful UAV control requires sensors used for attitude estimation to have good performance especially in mobile and temperature-varying environments [75]. Arduino is an open-source electronics platform found in a wide variety of application projects. The board is capable of reading inputs from various sensors and generates required outputs. It comes comes with different processors and board sizes.

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Fig. 6 Quadrotor cross and plus Configuaration. Picture reprinted from [82]

Arduino Nano was used in [76] to develop an instrumentation system to collect flight data such as airspeed, orientation, and altitude, e.t.c. The system will then transmit the flight data over a radio frequency module.

2.5 Rotors configuration There are different types of drones, they can generally be categorised as single rotor helicopter, fixed wing and multi-rotor drones [77,78]. Nowadays researchers endeavors to combine the advantages of fixed wing and multi-rotor drones [77]. Fixed wing drones are renowned for their endurance whereas helicopters and multirotors have the the advantage of VTOL as well as hovering. Quad-rotor drones are most common and belongs to the multi-copter family [77]. The quad-rotor unmanned aerial vehicle (UAV) are drones with four rotors typically designed in a cross configuration with two pairs of opposite rotors rotating clockwise and the other rotor pair rotating counter-clockwise to balance the torque. The roll, pitch, yaw and up-thrust actions are controlled by changing the thrusts of the rotors using pulse width modulation (PWM) to give the desired output [79]. Typically, the structure of a quad-rotor is simple enough, which comprises four rotors attached at the ends of arms under a symmetric frame. The dominating forces and moments acting on the quadrotor are given by rotors, driven with motors, mostly brushless DC motors. There are two basic types of quadrotor configurations; plus and cross configurations [80]. The difference between these configurations is where the front of the quadcopter is located. To counteract reactional torque due to propeller rotation, two diagonal pair of motors (1 and 2) rotate anticlockwise while the other pair, motors (3 and 4), rotate clockwise [80]. In contrast to the plus configuration, for the same desired motion, the cross-style provides higher momentum which can increase the maneuverability performances, each move requires all four blades to vary their rotation speed [81]. However, the attitude control is basically analogous. Figure 6 shows the quadrotor cross and plus configurations respectively. The red cross depicts direction to the front of the quadrotor, in this case to the right of the pictures in the figure. The quad-rotors translational motion depends on the tilting of rotor craft platform towards the desired orientation.

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Hence, it should be noted that the translational and rotational motion are tightly coupled because the change of rotating speed of one rotor causes motion in three degrees of freedom. This is the reason that allows the quad-rotor with six degrees of freedom (DOF) to be controlled by four rotors; therefore the quad-rotor is an under actuated system [83]. In principle, a quad-rotor is dynamically unstable and therefore proper control is necessary to make it stable. Despite the unstable dynamics, it has good agility. The instability comes from the changing rotor craft parameters and the environmental disturbances such as wind. In addition, the lack of damping and the cross-coupling between degrees of freedom make it very sensitive to disturbances.

2.6 Sensors used Essential to drone flight is the Inertial Guidance System, this is an electronic system that continuously monitors position, velocity and acceleration by means of incorporated sensor set. It consists of 3-axis rate gyro and 3-axis accelerometer as well as a magnetometer. The IGS readings are filtered to estimate the attitude of the UAV. Recent developments in computing and MEMs technology has seen the decrease in size of IGS sensors [84]. Thus for small UAVs, a micro IGS can be used to provide a complete set of sensor readings [75]. Attitude information can also be estimated using infrared (IR) thermopile sensors. They work on the fact that the earth emits more IR than the sky by measuring the heat difference between two sensors on one axis to determine the angle of the UAV. Other sensors such as Vision sensors, either by themselves or combined with inertial measurements sensors can also be used for attitude estimation [85].

3 Required software components for real-time implementation Real-time control requires hardware and software systems to be implemented together. Several definitions for real-time systems can be found in the literature. A good definition that we found states that; “a real-time system is one in which the correctness of a

result not only depends on the logical correctness of a calculation but also upon the time at which the result is made available" https://www.ibm.com. There is a time requirement, referred to as a deadline, under which the system tasks must be performed. The primary objective is to ensure a timely and deterministic response to events. In the context of drone control, such tasks are normally intended to react to external events in real-time. Thus such real-time tasks are required to keep up with external changes affecting drone performance. Tasks required to meet their deadlines to avoid catastrophic consequences are called hard real-time tasks.

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When meeting the deadline is desirable but not mandatory, the task is considered soft real-time task [86].

3.1 Real-time operating systems A real-time operating system (RTOS) provides services such as multitasking, scheduling, inter-task communication, etc., to facilitate the implementation of real time-time systems [87]. An RTOS is the key component needed to build a real-time system. Other software pieces such as compilers, linker, debugger and drivers are necessary to interface with system hardware: https://www.ni.com. RTOSs are employed in the development of many applications such as Internet of Things (IoT), automotive , medical suystems, robotics, industrial automation, avionics, and flight control systems [88,89]. RTOSs mainly focus on task predictability and efficiency, therefore have features to support timing constraints for application tasks [90]. There are several categories of RTOS; small, proprietary kernels as well as real-time extensions to commercial time-sharing operating systems such as Unix and Linux. The kernel is the core, an essential center of the RTOS, or any computer operating system. It is responsible for memory management, processing, and task management, and to interface with hardware and application software. Small, proprietary kernels are often used in embedded applications when very fast and highly predictable execution must be guaranteed. Meeting time constraints requires kernels to be small in size, which reduces RTOS overhead. Kernels must also have a fast context switch, support for multi-tasking, priority-based preemption, provide a bounded execution time for most primitives, and maintain a high-resolution real-time clock [90].

3.2 Scheduling and prioritisation Appropriate task scheduling in real-time applications is the basic mechanism adopted by an RTOS to meet time constraints of tasks [90]. It is the responsibility of the application developer to choose an RTOS that will schedule and execute these tasks to meet their constraints. For a given application, if a set of tasks can be scheduled such that they all meet their deadline, then the tasks are said to schedulable [91] In priority-driven (PD) scheduling, priorities are assigned to tasks. A task with the closest deadline than any other task is considered the highest priority task [92]. Embedded time critical applications employ the real-time scheduler to ensure low latency and meeting time constraints. Numeric priorities are assigned to threads constituting tasks, and only the highest priority task is selected to run by the scheduler. A higher priority task can preempt a lower priority task at any point of its execution [93]. However task priorities can also be dynamic such that a low priority task may temporary elevates its priority to

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prevent interruption during execution of its critical section. Preemption thresholds can also be set by considering task priority as well as task urgency. Both priority and Urgency are quantified such that it is possible for urgency to take precedence when scheduling tasks [86,93]. Multithreaded parallel programming systems (MPPS) has a characteristic that data is shared among threads. It is important that access to shared data is controlled to avoid associated concurrency errors. As an example, suppose a task alters or updates a global variable, it is necessary for the task to have exclusive access to that variable while it is executing, otherwise concurrent access to the same variable by other tasks will lead to data races, leading to miscompilations.Access of shared data by one task at a time can be achieved by use of Mutual exclusion locks (mutexes) [93].

3.3 Sensor inputs and feedback control The common drone platform has a specialised software running on a computer at the ground control station. It allows users to monitor and send control messages to affect drone's state and actions remotely. Aboard the drone, the autopilot software combines operator inputs and sensor feedback information to directly control UAV actuators [94]. Sensors onboard the UAV provide feedback data essential to determine the drone's position and attitude. A stereo camera was proposed for obstacle avoidance as well as velocity estimation in [95]. In [96], vision and IMU sensors were employed for automatic navigation

and landing of an AR drone quadrotor. A landing marker was positioned in the drone frontal camera's sight of view, see Fig. 7. The landing marker position is the desired position X d = (xdG , ydG , z dG), which corresponds to a height above the landing marker. Position X = (x G , yG , z G) denotes the drone current location. The position error is then denoted as E = X d − X , where E = (ex , e y , ez). The symbols ex , e y , ez are position errors in directions X G , YG , and Z G , respectively. The PID controller was applied to the position error in accordance with (1) and (2). The drone will land when above the marker, i.e., when the error E = 0. t d xG + Ki x ex dt (1) dt 0 t dyG + Ki y Vy = K py e y − K dy e y dt, Vz = K pz ez (2) dt 0 Vx = K px ex − K d x

3.3.1 Localisation using differential global positioning system (DGPS) Differential global positioning system (DGPS) is extensively used for accurate localisation of drones. The scope of localization and mapping for an agent is the method to locate itself

Fig. 7 Automatic navigation and landing of an AR drone quadrotor. Picture reprinted from [96]

Fig. 8 Schematic diagram for on-board smartphone flight controller using Arduino Mega to interface with the electronic speed controllers (ESCs). Picture reprinted from [101]

locally, estimate its state, and build a 3D model of its surroundings, by employing among others vision sensors [97]. Towards this direction, a visual pose-estimation system from multiple cameras on-board a UAV, known as multi-camera parallel tracking and mapping (PTAM), has been presented in [98]. This solution was based on the monocular PTAM and was able to integrate concepts from the field of multicamera ego-motion estimation. Additionally, in this work, a novel extrinsic parameter calibration method for the nonoverlapping field of view cameras has been proposed. 3.3.2 Mobile phone technology in UAV applications UAV applications encompass many areas, including, aerial surveillance ,reconnaissance, underground mine rescue operations, and so on [25,99]. Some of these application areas are GPS denied, thus GPS can not provide the location for a UAV. Currently, vision sensors, laser scanners, and the IMU are the most common position sensors used for UAV selflocalisation. In some applications, small UAVs are preferred for their cost and high maneuverability. Considering the limited load capacity and the cost of small UAVs, it cannot be equipped with sensors of high precision and large volume [100]. Micro-electro-mechanical system (MEMS) sensors are therefore preferred alternatives because they are small and cheap. On the other hand, mobile phones contain multisensors, multi-core processors, have a small volume, and lightweight. In [101], Nexus 4 smartphone developed by Google, was used as a flight controller. The phone is equipped with inbuilt MEMS sensors such as accelerometer, gyroscope, magnetometer, global navigation satellite system (GNSS), and barometer. The implementation exclusively used sensors and processors from the smartphone, see Figs. 8 and 9. Mobile phone usage possibilities in UAV platforms are further elaborated in [102], where a smart phone is proposed for implementation of drone control algorithms. The usage of smart phones can reduce development time as it

Fig. 9 Quadcopter used in [101] with an on-board smartphone as flight controller. Picture reprinted from [101]

it cuts down the need for integration of different drone hardware components, instead the proposed solution uses smart phone inbuilt sensors [102]. 3.3.3 Communication to the ground control station Communication to the ground control station allows drone pilots to remotely configure mission parameters, such as coordinates to cover during way-point navigation and the action to take at each way-point. Most existing drone platforms have the configuration shown in Fig. 10. A specialized software runs at a ground-control station (GCS) to let users configure mission parameters. The Ground Control Station is a system made up of software and hardware necessary for UAV remote control. Hardware, such as the joystic, takes the pilot's command which is transmitted to the drone via radio transmitter. The GCS software collects tellemetry data transmitted from the UAV and displays it the on the GCS user interface [103]. Communication networking is responsible for the information flow between GCS and UAV on a mission. It needs to be robust against uncertainties in the environment and quickly adapt to changes in the network topology.

which schedules tasks according to earliest deadline first (EDF) precedence [109] is an example of an offline scheduling algorithm. By contrast, online scheduling algorithms schedule tasks at run-time.An online scheduling algorithm that encoporates event-driven and periodic rolling strategies (EDPRS) is discussed in [110].

4 Types of controllers

Fig. 10 Platform for drone control from GCS . Picture reprinted from https://www.google.com/search?q=multirotor+UAV++ground+ control+station+images

Communication is not only needed for disseminating observations, tasks, and control information but also needed to coordinate the vehicles more effectively toward a global goal. The goal could be tasks such as areal monitoring or detecting events within the shortest time, which are especially important in disaster situations. Some specific issues that need to be addressed [41] are connectivity, routing-and-scheduling, communication link models, and data transmission.

3.4 Real-time scheduling algorithms Real-time scheduling aims to complete tasks within specific time constraints and avoiding simultaneous access to resources shared amongst application tasks. To guarantee real-time performance while meeting all timing, precedence and resource usage specifications requires employment of efficient scheduling algorithms supported by accurate schedulability analysis techniques [104]. Real-time scheduling algorithms can be implemented for uniprocessor or multiprocessor systems [105–107]. In the context of drone applications, an example could be implementing a flight control system using Arduino Uno or other single processor boards. The Arduino Uno uses the ATMEGA 328P processor (uni-processor), whereas embedded computers like the Rasberry-Pi uses a quad core ARM Cortex-A72 processor (multi-processor). Scheduling algorithms can be broadly divided into two major subsets: offline scheduling and online scheduling algorithms [104]. In offline scheduling algorithms, task scheduling is carried out before system execution, also known as pre-run time scheduling. The scheduling information is then employed during runtime. The YDS algorithm (named after the author) [108],

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UAV control requires an accurate and robust controller for altitude as well as velocity-and-heading [111].The altitude controller drives the UAV to fly at the desired altitude, including landing and take-off stages. The heading and velocity control enables UAV to fly through desired waypoints [112]. To achieve the above control requirements, different control strategies such as Fuzzy Logic,Linear Quadratic Regulator (LQG), Sliding Mode Control (SMC), Proportional Integral Derivative (PID), Neural Network (NN), e.t.c can be used. Robust control systems have been widely developed to address parametric uncertainties and external disturbance. In case of multirotor UAVs uncertainties arising from propeller rotation, blades flapping, change in propeller rotational speed and center of mass position dictates the need for a robust nonlinear controller [113]. In [113] robustness as well as compensation forsysten nonlinearities was adresses by combinig the nonlinear sliding mode control (SMC), robust backstepping controller and a nonlinear disturbance observer (NDO). The backstepping controller stabilised translational movement while the SMC controlled the rotational movement of the quadrotor. The NDO provided all the estimates of disturbances ensuring robustness of the feedback controls. The PID controller was compared with a neural network controller, specifically the direct inverse control neural network (DIC-ANN) in [114]. The comparison was done in simulation, where both controllers were excited with the same reference altitude reference input and their performances plotted together.The simulation aimed to mimic a quadrotor flight in four phases comprising take-off and climb phase at $0 < t < 10$ s, hovering phase at $10 < t < 20$ s, climb in ramp phase at $20 < t < 22.5$ s, and lastly the final altitude phase at $22.5 < t < 50$ s. The comparison results showed that the DIC-ANN performed better than the PID controller in handling quadrotor altitude dynamics.Also at hovering conditions the DIC-ANN exhibited less steady state error as compared to the PID controller and the transient oscillations damped faster with the DIC-ANN showing that it handles nonlinearities better than the PID controller. PID controllers are widely used in autopilots due to their ease of implementation, how ever they have limitations when operating in unpredictable and harsh environments. In [115] the performance of and acuracy of an attitude controller was

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investigated. The attitude controller is a neural network (NN) based controller trained through reinforcement learning (RL) state of the art algorithms, the Deep Deterministic Policy Gradient (DDPG), Trust Region Pocy Optimisation (TRPO), and the Proximal Policy Optimisation (PPO). The NN controller performance was compared to the performance of a PID controller to determine the appropriacy of NN controller in high precision, time-critical flight control. The contoller performance was evaluated in simulation using GYMFC environment. The results showed that RL can trail accurate attitude attitude controllers, also the controller trained with PPO outperformed a fully tuned PID controller on almost every metric. The linear quadratic regulation (LQR) optimal control algorithm operates a dynamic system by minimizing a suitable cost function [79]. When the LQR is used with linear quadratic estimator (LQE) and Kalman filter, it is then referred to as the linear quadratic Gaussian (LQG) The LQG was applied in [116] for altitude control of a quadrotor micro aerial vehicles (MAVs). Ignoring air resistance, the linearized model for altitude control problem was obtained as (3), the state space model is represented by (4) , while the cost function is given by (5), also refered to in [116] as the quadratic form creterion. The control objective is to determine the control input U (t) to minimise cost function [79]. F − mg m

d x(t) ẋa (t) = dt xr (t)

B 0 A 0 x(t) + u(t) + r (t) = 0 I −C 0 xr (t)

0 = A∗ xa (t) + B ∗ u(t) + r (t), I

Z̈ = a =

(3)

(4)

where

A 0 B , B∗ = . −C 0 0

1 ∞ T J = [xa Qxa (t) + u T (t)Ru(t)] dt. 2 0

A∗ =

(5)

The linear Quadratic regulator with and integral with an integral term (LQTI) and a model predictive controller were employed to develop an automatic carrier landing system for a UAV [117]. The LQTI was applied to the coupled multiinput multi-output (MIMO) UAV dynamic model to reduce steady stare error while the model predictive controller was applied to the final phase landing of the UAV. Automatic carrier landing was performed sequentially by the two controllers. The LQTI controller was applied up to a few seconds before touch down followed by the MPC controller during

Fig. 11 Drone path planning from start 1 and Start 2 to Goal, shortest path taken from both starting points. Picture reprinted [127]

the final stage of landing. The controller was verified via simulations on HSS Hydro toolbox. Simulation results indicated that the proposed carrier landing system can improve landing accuracy. The performance of the controllers indicted that the LQTI is suitable for calm sea environments while the MPC performs better even in rough sea environments [117]. Some implementations for UAV control employ the sliding-mode control (SMC) strategy. Sliding-mode control is a nonlinear control method that that utilises a high-frequency switching control signal to the system to command it to slide along a prescribed sliding manifold [118,119]. It encompasses a broad range of varying fields, from pure mathematical problems to application aspects [120] (Fig. 11). An SMC based fault tolerant control design for underactuated UAVs was implemented on a quadrotor in [121]. The design approach separated system dynamics into two sub-systems, a fully actuated and an under-actuated subsystem. A Nonsingular Fast Terminal Sliding Mode Controller (NFTSMC) was then designed for the fully actuated subsystem, the Under-actuated Sliding Mode Controller (USSMC) was then derived for the under-actuated subsystem. The controller performance, on a quadrotor platform, demonstrated excellent robustness to actuator faults, disturbances. It had fast convergence and high precision tracking. Herrera et al. designed a sliding-mode controller and applied it in simulation of a quadrotor. They considered a PD sliding surface for vertical take-off and landing. Broad coverage of control algorithms for quadrotors can be found in [79,122–124]. Figures 12, 13 and 14 shows the PID, LQG, and SMC controllers applied to a quadrotor respectively.

5 Path planning Missions of UAVs usually involve travelling from some initial point to a goal point [125,126]. A mission requires

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generating a path for the UAV to follow. Path planning is one of the main aspects of autonomous navigation [127]. The path planning problem is to produce a path or set of waypoints for the drone to follow while taking into account the environmental and physical constraints of the drone in order to achieve a collision free flight [128,129]. This is obstacle avoidance while executing the the UAV's mission. Figure 11 depicts drone paths from start to goal position for two drones launched from different locations, each calculating its best path to reach the goal position. In the literature pertinent to UAV path planning, several algorithms for measuring distances to obstacles and calculations of the drone's path are suggested [130–132]. An optimal flight path planning mechanism to determine the best path of the UAV was developed in [133]. Consideration of environmental information such as geographical topology,location dependent wireless communication channel statistics and flight risk, sensor node deployment and worth of sensing information for different sensor types was made. The implementation aimed at determining the best path to maximise the value of gathered sensing information as well as to minimise flying time, energy consumption, and UAV operational risks. In [127], 3D propagation approximate Euclidean distance transformation algorithm was formulated to achieve safe path planning by calculating a 3D buffer around the obstacles. The algorithm prevents the drone from flying too close to obstacles by setting the minimal distance from obstacles according to the size of the drone. The algorithm is also used for drone path planning in [127]. It is worth noting that current techniques for UAVs path planning are application dependent. Different applications require different path-planning approaches. A method to enhance massive unmanned aerial vehicles for mission critical applications (e.g., dispatching many UAVs from a source to a destination for firefighting) is investigated in [134]. The method aims to achieve UAV fast travel while avoiding inter-UAV collision while executing their mission. The path planning problem is tackled by exploiting a mean-field game (MFG) theoretic control method. The method requires UAV state exchange only once at launch, thereafter each UAV controls its acceleration by locally solving two partial differential equations, the Hamilton-Jacobi-Bellman (HJB) and Fokker-PlanckKolmogorov (FPK) equations. Due to high computational burden posed by solving the partial differential equations, two machine learning models were used to approximate the solutions of the HJB and the FPK. The performance of the proposed method was validated on simulation, showing that the mean-field game method guarantees UAV collision avoidance. Also for the proposed approach, the effectiveness of the mean field game method is determined by the level of the HJB and FPK training.

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6 UAV real-time control implementation In order to implement real-time control for UAVs, tasks have to be defined. An RTOS is required for tasks scheduling, inter-task communication, and management of available resources such memory, and power consumption [135–137]. Each task is allocated a memory space, called a stack, in the microprocessor. This is enabled by the RTOS kernel's support for multi-threading [138,139]. Scheduling and prioritisation of tasks, as well as the update frequency of the sensors providing essential data for task execution, ensure that application time constraints are met [140]. In [141], an embedded RTOS (RT-Thread) is applied to a quadcopter to address problems of real-time response, heavy workload and difficulty in control. Practical tests in this work indicated that quadcopter control system based on RT-Thread responded real-timely, and ensured smooth flight with a PID control algorithm. The application tasks defined in this work are attitude information acquisition, attitude information fusion, and PID control. The latter is for quadcopter control. The application task is developed on top of RT-Thread RTOS running on STM32F407VGT6 microprocessor. The processor is equipped with high-performance ARM Cortex-M4 core with maximum system frequency of 168MHz, an FPU (floatingpoint unit), 1 Mbyte of flash, and 192 Kbytes of SRAM. It has peripherals such as ADC, SPI, USART, controller area network (CAN) bus, DMA, etc. High operating frequencies and high-speed memory provide high computational power to enable quadcopter complex calculations to be performed. Also additional peripherals reduce the need for external IC and reduce computational burden from the microprocessor. The implementation in [142] uses a dual processor configuration. One processor is used for telemetry and another for control of a custom quadcopter used as a test-bed. The telemetry processor executes

software tasks such as communicating reconfiguration and monitoring data with the GCS, data collection from sensors, and wirelessly transmitting data to the GCS. The tasks are managed by μC/OS-II™, an RTOS. The control processor runs the PID controller algorithm for the quadcopter stabilization and navigation. This task was achieved through several tasks allocated to the control processor. Tasks include reading GPS, compass, IMU, and altitude sensor data received from the telemetry processor. Other tasks include implementation of the roll, pitch, yaw, and altitude PID control loops, and communicating reconfiguration and monitoring data with the telemetry processor via CAN bus. Figure 15 shows the PID controllers used in the implementation.

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Fig. 12 Block diagram of PID controller applied to a quadrotor [79]

Fig. 13 Block diagram of LQG controller applied to a quadrotor [79]

Fig. 14 Block diagram of an SMC controller applied to a quadrotor [79]

Fig. 15 PID control loops implemented by the control processor. Picture reprinted from [142]

7 Essential components for UAV real-time applications 7.1 Real-time operating system (RTOS) The literature pertaining to real-time implementation of drone control systems is relatively limited, and the number of reported studies on UAV scheduling has been minimal [143]. The main feature of real-time implementation in drones control is that an embedded RTOS, also referred to as UAV

operation system in some literature, is required [67,144]. The RTOS provides a real-time kernel on which the control program running on a micro-controller is implemented. The real-time kernel guarantees application tasks meet their time constraints by employing the UAV scheduling system [143]. Consequently, a Real-Time Operating System (RTOS) that provides operating environments for various mission services on UAVs is crucial [145]. The commonly used RTOS for UAVs is FreeRTOS, and an empirical study of this RTOS was conducted in [145]. The study looked at aspects such as functionality changes during the evolution of FreeRTOS. A total of 85 releases of FreeRTOS, from V2.4.2 to V10.0.0 were considered.

7.2 Microcontroller The microcontroller is the UAV onboard processing unit for UAV computations and UAV state monitoring [146,147]. It is selected such that it matches application task requirements. Considerations such as computational speeds and communication with onboard sensors have to be made. Palossi et al. [146] extended the hardware and software of a 27 grams nano-size, commercial off-the-shelf (COTS) quadrotor, the crazyflie 2.0, to achieve object tracking capability.

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Table 1 Summary of Components for Real-time Control Implementation RTOS

Hardware required

Controller used

Sensors used

References

RT-Thread

STM32F407VGT6 processor

PID

MPU-6050 (an IMU)

[141]

ERIKA Enterprise

dsPIC 30F6014 micro-controller

PID

3 gyroscopes (one for each axis); 3-axis accelerometer; inclinometer; GPS module

[148]

FreeRTOS

AVR XMEGA

PID

IMU

[149]

µC/OS-IITM

Two Freescale HCS12 microcontrollers

PID

IMU; GPS; Compass

[142]

QNX Neutrino

PC/104 (CRR3-650, Lippert); DIAMOND-MM-32-AT data acquisition board

-

Crossbow NAV420 combines GPS and IMU

[149]

1 RTOS—Real-Time Operating System; ERIKA—Embedded Real tIme Kernel Architecture; µC/O S − I I —Micro Controller Operating SystemII

8 Conclusion

Fig. 16 Sensors connected to microcontroller. Reprinted from [150]

The quadrotor platform consists the STM32F405 microcontroller as the main onboard processing unit, the Nordic nRF51 module for wireless communication. The STM32 is an ARM Cortex-M4F microcontroller, operating at 168MHz. The onboard sensing is performed by a 9-axis IMU, the MPU-9250 with a gyroscope, an accelerometer, a magnetometer, and an ST LPS25H pressure sensor with a typical accuracy of ±1 meter. The vehicle is powered by a 240mAh Li-Po battery.

Real-time control of drones requires an embedded RTOS for implementation. The RTOS provides facilities such as multi-threading, scheduling and priority assignment. These support real-time response of the drone control system to feedback from GPS and IMU. The drone control system subsequently apply the corresponding motor speeds to achieve the desired drone's movements. Multitasking enables tasks, such as position and orientation feedback, path-planning, and control implementation to run in parallel. This facilitates realtime response of the drone. Tasks may need results from other tasks for their computations. Scheduling and prioritisation of tasks ensures that at any point in time critical tasks are given computational resources by the microprocessor. For example obstacle avoidance is the highest priority task to ensure that the drone does not collide with other drones as well as other obstacles. Acknowledgements The authors would like to acknowledge the funding support on this work from the Botswana International University of Science and Technology (BIUST) Drones Project with project number P00015. The authors would also like to thank Boyce Segweni for his help in the preparation of this manuscript.

Compliance with ethical standards Conflict of Interest All authors declares that they have no conflict of interest.

7.3 Sensors and actuators In UAV applications several sensors and actuators are connected to the microprocessor for UAV control. Table1 highlights the vital components for real-time implementation of UAV control, the table also lists various sensors used. Figure 16 shows the UAV onboard sensors used in a fire fighting remote-sensing system in [150]. Various sensors as well as the overall connection network is depicted.

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Review

A Review of Indian-Based Drones in the Agriculture Sector: Issues, Challenges, and Solutions Ranjit Singh 1

and Saurabh Singh 2, * 1

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Abstract In the current era, Indian agriculture faces a significant demand for increased food production, which has led to the integration of advanced technologies to enhance efficiency and productivity. Drones have emerged as transformative tools for enhancing precision agriculture, reducing costs, and improving sustainability. This study provides a comprehensive review of drone adoption in Indian agriculture by examining its effects on precision farming, crop monitoring, and pesticide application. This research evaluates technological advancements, regulatory frameworks, infrastructure, farmers' perceptions, and the financial accessibility of drone technology in the Indian agricultural context. Key findings indicate that, while drone adoption enhances efficiency and sustainability, challenges such as high costs, lack of training, and regulatory barriers hinder widespread implementation. This paper also explores the growing market for agricultural drones in India, highlighting key industry players and projected market growth. Furthermore, it addresses regional differences in adoption rates and emphasizes the increasing social acceptance of drones among Indian farmers. To bridge the gap between potential and practice, the study proposes several policy and institutional recommendations, including government-led financial incentives, training programs, and public–private partnerships to facilitate drone integration. Moreover, this review article also highlights technological advancements, such as AI and IoT, in agriculture. Finally, open issues and future research directions for drones are discussed. Academic Editor: Yiannis Ampatzidis Received: 18 June 2025 Revised: 4 August 2025

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Sensors 2025, 25, 4876

- Introduction With the global population expected to reach 9.7 billion by 2050, the demand for food is projected to rise significantly [1]. India is the second-largest food producer worldwide [2] and relies heavily on agriculture, which is the primary livelihood for its rural population. However, this sector faces many challenges, including small landholdings, unpredictable weather, low productivity, and dependence on traditional farming methods. To elaborate, the agricultural industry has been slow to adopt the latest technological advancements. The main obstacles include crop loss caused by unpredictable weather and uncontrolled pest attacks. Many Indian farmers still depend on seasonal monsoon rains for irrigation and continue using traditional farming practices. Additionally, Indian agriculture faces other issues, such as structural hurdles that lead to low productivity, like minimal landholdings

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that are often not profitable [3]. The average farm size in India is much smaller (around 1.08 hectares) compared to countries like the USA, Australia, and European nations [4]. Despite having smaller farms, many Indian farmers have limited access to essential inputs such as water, fertilizers, and electricity, mainly due to economic and infrastructural constraints. Furthermore, there is minimal automation, including the use of tractors, harvesters, drip irrigation, and similar technologies. Indian agricultural yields are among the lowest globally, due to factors like low soil fertility, insufficient fertilizer use, and traditional farming practices.

Additional challenges include soil degradation, overuse of leguminous and fodder crops, and unscientific farming methods, all of which increase the difficulties faced by farmers [5]. The government of India has set an ambitious goal to double farmers' income in the coming years [6], creating an urgent need for improvements in this field. The agricultural sector must begin adopting precision agriculture to enhance farmers' productivity. To overcome these challenges, Indian agriculture needs to embrace advanced technology. Among these innovations, drones have become transformative tools that offer precision agriculture capabilities, lower costs, and support environmental sustainability. As shown in Figure 1, the Indian drone market, which includes both commercial and non-commercial applications like agriculture, defense, healthcare, infrastructure, and surveillance, is expected to grow from USD 1.2 billion in 2023 to USD 4.87 billion by 2030, at a compound annual growth rate (CAGR) of 22.15% [7]. This rapid expansion is fueled by increasing demand for drones in precision farming, land surveys, and disaster response, along with strong government support through initiatives like the Production-Linked Incentive (PLI) scheme for drone manufacturing. Although this projection encompasses the entire UAV market in India, agriculture remains a key area of growth due to its potential to reduce labor costs and boost efficiency in farm management.

Figure 1. Projected growth of the Indian drone market [7].

Drones enable farmers to increase crop yields and promote environmental sustainability through precision agriculture and innovative farming methods. They help cut costs by reducing manual pesticide spraying expenses and lowering pesticide exposure for workers [8]. Drones allow for efficient and fast pesticide application, improving pest control and decreasing environmental pollution. India's diverse agro-climatic zones result in varied cropping patterns and agricultural practices [9]. This diversity necessitates specialized solutions for crop monitoring and management, making drones an effective tool for precision agriculture across various regions. Additionally, drones are equipped with sensors that enable crop health monitoring throughout

the growing season, allowing farmers to make timely interventions based on assessments of nutrient deficiencies and pest attacks. With increasing water scarcity in many Indian regions, efficient water management becomes essential [10]. Drones can help monitor soil moisture levels and crop health, enabling farmers to optimize irrigation practices and conserve water resources. Additionally, pest and weed prevalence continue to challenge Indian agriculture [11]. Drones serve as an early warning system for disease detection, weed management, and the identification of issues before visible symptoms appear. Furthermore, drones provide real-time, high-quality aerial imagery that surpasses satellite imagery and helps assess soil properties. The use of drones ensures need-based, precise, and focused applications for crop inputs, such as determining the correct amounts of fertilizers and pesticides to use, identifying areas for irrigation, assessing production readiness, and locating areas for planting and harvesting. This can be performed in real time using minimal resources. Beyond current use cases, drones are expected to play a crucial role in the transition to Agriculture 4.0, which emphasizes integrating the Internet of Things (IoT), big data, artificial intelligence, and robotics throughout the entire agricultural production and supply chain [12]. Global trends show promising results. Countries like the United States and Japan have demonstrated how drones can boost agricultural productivity. However, India's specific challenges, such as small farm sizes and limited access to technology, call for customized solutions suited to its socioeconomic and agro-climatic conditions. Recent research by Trappery et al. in the field of agricultural drones discussed the specifications, advantages, and disadvantages of drones in agriculture [13]. This study offers valuable insights into technological advancements, operational capabilities, broad benefits, and limitations of drone usage, highlighting state-of-the-art developments and future R&D trends in agricultural UAV technologies. However, it does not sufficiently address the specific needs of small-scale farmers worldwide, leaving a gap in understanding how drones can be effectively adapted to different socioeconomic contexts. Additionally, several research studies specific to the Indian agricultural context, such as drone benefits, economic aspects, and regulatory policies, were selected and analyzed, as shown in Table 1. These studies offer valuable insights into the advantages of drones across various sectors (Gupta et al., Katekar et al., Puppala et al., Ramanjaneyulu et al.), economic impacts (Katekar et al., Puppala et al., Ramanjaneyulu et al.), infrastructure development (Katekar et al., Puppala et al., Goyal et al.), and more. Among these, Puppala et al. stand out by providing a detailed categorization and ranking of barriers that hinder drone adoption among

Indian small-scale farmers. Their study identifies six major types of barriers: economic, operational, regulatory, social, behavioral, and infrastructural, based on a hybrid multi-criteria framework combining Fuzzy Delphi and AHP methods. The findings emphasize that high initial investment and component costs are the most critical issues, followed by a lack of skilled operators, unclear policies, limited-service infrastructure, and insufficient awareness. Concerns over automation-related job displacement and region-specific challenges like weather and no-fly zones were found to be moderately significant. These results are validated by experts and supported by existing literature, reinforcing the urgency of addressing economic and operational gaps to ensure successful drone integration in Indian agriculture. Similarly, Yadav et al. discussed the current state of agricultural drone technology, including crop health monitoring and farm activities such as weed control, evapotranspiration estimation, and spraying [14].

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Table 1. Comparison of existing drone review articles. Review Articles

Gupta et al. [15]

Katekar et al. [16]

Puppala et al. [17]

Ramanjaneyulu et al. [18]

Goyal et al. [5]

Our Review Article

Drones' benefits

Yes

Yes

Yes

Yes

No

Yes

Economic and practical aspects mentioned (cost, training, job impact)

No

Yes

Yes

Yes

Partially

Yes

Challenges and limitations

No

Yes

Yes

Partially 1

Yes

Yes

Internet connectivity, infrastructure development

No

Yes

Yes

Partially

Yes

Yes

Case studies

No

Yes

Yes

Yes

Yes

Yes

Regulatory policies and laws

No

No

Yes

No

No

Yes

Research solutions mentioned

No

No

Yes

Yes

Yes

Yes

Drone categorizations in India

No

No

No

No

No

Yes

1 “Partially” signifies coverage of at least one but not all identified sub-factors: (1) Ramanjaneyulu et al. [18]

covered cost savings (reduced spraying costs) and drudgery relief (reduced labor burden), but did not address training, job impacts, infrastructure, or environmental impact. (2) Goyal et al. [5] primarily addressed cost challenges, while training, job impact, and other practical aspects remain unexamined.

Although these points are essential, their discussion does not thoroughly explore the challenges. However, these studies often lack comprehensive practical insights into the economic feasibility for smallholders. Furthermore, most studies do not consider training and certification, which are necessary for farmers and drone operators, since flying a drone requires specific skills [19]. Operational challenges such as battery life and payload capacity are also overlooked. Additionally, regulatory issues under current policies and the infrastructure for drone operations remain underexplored. This study aimed to address these gaps by providing an in-depth analysis of the economic, regulatory, and technological aspects of drone adoption in

Indian agriculture. It assessed the opportunities and challenges of drone integration, especially for small-scale farmers. Moreover, this study features region-specific case studies from Punjab and Rajasthan to examine how drones are practically used in Indian farming. In doing so, it offers practical recommendations for policymakers, technology developers, and agricultural stakeholders to promote the scalability and long-term sustainability of drones in Indian agriculture. To frame these interconnected issues, a conceptual framework has been developed in Figure 2, illustrating the dynamic relationship between government support, training programs, and farmer adoption. This framework highlights how policy incentives and skill development initiatives influence the adoption of drone technology, and how farmers' experiences can inform future policy and program improvements. It serves as a guiding structure for the review and analysis presented throughout this paper. 1.1. Contributions and Motivation The research presented in this study explores the economic, regulatory, and technological progress related to the adoption of drone technology in Indian agriculture. It fills existing gaps in the literature concerning the feasibility and practical application of drones in farming. The key contributions of this study are as follows.

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This paper examines the widespread challenges faced by Indian farmers, based on the findings of numerous existing studies. It also highlights the main barriers to drone adoption in Indian agriculture, such as high costs, lack of technical training, regulatory obstacles, and poor infrastructure. This study provides valuable insights into the obstacles confronting small-scale farmers and the agricultural sector. The paper explores government initiatives and policies that promote drone use in agriculture, including financial assistance programs and regulatory reforms.

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The paper also explores various technological advancements, such as AI and machine learning integration, IoT-based monitoring, and solar-powered drones, along with policy solutions to tackle the identified challenges. This study explores real-world case studies and examines successful drone technology implementation in Indian agriculture, providing insights into cost-effective and scalable solutions. The survey offers insights into drones' current and future market growth in India, along with the entities that are currently using drones for various purposes. It also highlights some open questions and research areas that can enhance drones' capabilities.

Figure 2. Conceptual framework illustrating the interaction between government policies, farmer adoption, and training in the agricultural drone ecosystem in India.

The motivation behind this study is the urgent need to modernize Indian agriculture using advanced technologies such as drones. While several previous studies have highlighted the benefits of drones in agriculture, few have provided comprehensive insights into their economic feasibility, regulatory challenges, and practical implementation for smallholder farmers. Despite government initiatives aimed at promoting drone technology, policy gaps still exist that hinder small-scale farmers' access. This study not only highlights the slow adoption of technological advancements in farming and the structural hurdles that lead to low productivity but also offers existing solutions and bridges these gaps by providing an in-depth analysis of drone adoption in Indian agriculture. 1.2. Organization of Paper The rest of the paper is structured as follows. Section 2 offers a thorough literature review, tracing the development of drones from military uses to agricultural applications. It discusses global trends in agricultural drones and their importance to India's farming sector. Additionally, this section covers the policies and regulatory environment regarding drone use in India, emphasizing government initiatives and research efforts. Section 3 explains the methodology applied in the study. It outlines the research approach, including the selection criteria for reviewed literature, data sources, and analytical techniques.

Section 4 provides an overview of the Indian agricultural drone landscape. It examines the current state of drone adoption in India, the main players in the agricultural drone industry, and the types of drones used in farming. This section discusses government initiatives, contributions from the private sector, and the economic impact of drones in agriculture. Section 5 highlights the issues and challenges related to drone adoption in Indian agriculture. It covers financial constraints, regulatory hurdles, lack of farmer awareness, and insufficient infrastructure as key obstacles. Also, it looks at the economic viability of drones for small-scale farmers and emphasizes the need for effective training programs. Section 6 examines technological and policy solutions to address the challenges identified earlier. It discusses advancements like AI and machine learning integration, IoT-based monitoring, and solar-powered drones for cost effectiveness. Additionally, it reviews policy recommendations such as government subsidies, training programs, and financial support initiatives to help small-scale farmers access drone technology. It also includes case studies of successful drone deployments in Indian agriculture. Finally, Section 7 concludes the work by summarizing the key findings, emphasizing the transformative potential of drones in Indian agriculture. It highlights the importance of continued investment in drone technology, regulatory support, and farmers' education to ensure the long-term success of drones in revolutionizing the agricultural sector. Additionally, it explores future research directions in drone technology for agriculture. Lastly, it concludes with an open discussion.

- Literature Review Drones have become transformative tools in precision agriculture, providing benefits such as better crop monitoring, targeted pesticide application, and increased productivity. This section reviews current research on agricultural drone adoption in India, emphasizing global advancements and their relevance to India's farming sector. The main areas covered include technological innovations, economic viability, regulatory frameworks, and the challenges faced by small-scale farmers in India. 2.1. Drone Adoption in India India operated its first drone in 1996 when the army acquired the Israeli Searcher Mark I. This marked the start of India's engagement with unmanned aerial vehicles (UAVs) for military uses. Following the army's lead, the Indian Air Force and Indian Navy also began to use drones in their operations within two years of the initial purchase. This early use mainly focused on gathering intelligence and reconnaissance. Over the years, India has advanced its drone technology, especially through efforts by organizations such as the Defense Research and Development Organization (DRDO) [20] and the National Aerospace Laboratories (NAL). The Rustom series of drones, including weapons-ready versions like Rust-II, is an example of domestic development aimed at replacing foreign models like the Israeli Heron [21]. The integration of drones into India's national security efforts became more prominent, drawing lessons from global military experiences, particularly from countries like Israel. Drones are now being used in agriculture for tasks like crop monitoring and pesticide spraying. Their use has gained significant attention worldwide and in India, where 70% of rural people are farmers. Since agriculture is a vital sector contributing 16% to India's GDP, the government is actively working to implement this technology across various agricultural sectors.

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2.2. Global Trends in Agricultural Drones Unmanned aerial vehicles (UAVs), also known as drones, have revolutionized various sectors, and agriculture is one of them. Drones have evolved from simple, remote-controlled machines to performing complex tasks in agriculture autonomously. The agriculture sector worldwide has seen major changes in recent years due to the rapid adoption of drone technology. Globally, the use of drones in agriculture has enabled precision farming, helping farmers leverage data and technology for sustainable practices. Additionally, the ability to monitor and map larger areas in just a few hours makes this technology particularly valuable for farmers. Drones can produce accurate, up-to-date maps of farmland, providing farmers with essential information about their fields. Moreover, drones play a crucial role in irrigation management, which is vital in areas with limited water resources. They help optimize irrigation, reduce water waste, and ensure crops receive adequate water. Furthermore, drone technology has become increasingly common in planting and seed sowing. For example, in Australia, drones are increasingly used for reforestation efforts, especially in regions affected by annual bushfires. These unmanned aerial vehicles (UAVs) are equipped to disperse seeds across large, inaccessible terrains, aiding in rapid forest restoration [22]. A variety of imaging tools, such as thermal cameras, multispectral sensors, and light detection and ranging

(LIDAR), can be mounted on drones to enable early detection of plant diseases. By capturing high-resolution aerial images, drones can identify subtle changes in crop health, allowing for timely intervention to prevent the spread of infections and reduce crop losses [23]. A comprehensive review indicates that as of December 2023, China and the USA have made significant contributions to research on UAV-based plant disease detection, with 25 and 18 research articles, respectively [24]. Developed nations have successfully adopted drone technology across various sectors; specifically, it has been reported that in Japan, drones conduct almost 90% of aerial crop dusting and spraying. The planning, design, and construction of rice irrigation systems, along with the implementation of irrigation scheduling, demonstrate the use of drones in precision agriculture in African countries such as Nigeria. The US government is also working on legislation that allows the use of drone technology in agriculture [25]. China has widely adopted drone technology in agriculture, especially in pesticide spraying. In 2021, more than 120,000 drones were used to spray pesticides over 175.5 million acres of farmland [26]. Along with the global adoption of drones, recent technological advancements have greatly improved drone capabilities across different industries. Key developments include the following. 2.2.1. Multispectral and Hyperspectral Imaging Multispectral and hyperspectral sensors on drones enable data collection at various wavelengths, allowing for a comprehensive analysis of environmental features. This method is especially useful in agriculture, as it helps with early disease detection and monitoring crop health. These sensors provide insights into plant physiology that are not easily visible to the human eye when examining wavelength bands [27]. 2.2.2. Artificial Intelligence (AI) and Machine Learning Integration New technologies like AI and ML improve their skills. Right now, there is a widespread AI boom globally. AI is making drones better at spotting weeds and pests, analyzing crop data, and giving advice on what fertilizers to use. Combining AI with drones also helps cut down on chemical use and reduces resource waste.

2.2.3. Thermal Imaging Drones equipped with thermal cameras can detect temperature changes, which is vital for tasks like identifying crop water stress and finding people during search and rescue operations. This capability allows operation in various environments, including those with limited visibility. 2.2.4. Enhanced Autonomy and Swarming Technology AI advancements have enabled the development of drone swarms that can operate independently and collaboratively. These swarms can work together without human help to perform complex tasks such as surveillance, emergency response, and large-scale environmental monitoring [28]. Because of these developments, drone usage has grown in recent years. As a result, several new companies have entered the agricultural drone market, which offers a wide range of drones and services. This increased competition reduces the cost of agricultural drones and makes them more affordable for farmers [29]. 2.3. Relevance of Drones in Indian Agriculture In India, most farmers have small landholdings, and external factors such as weather, soil conditions, and temperature significantly influence farming. Agricultural drones enable farmers to adapt to specific environments and make informed decisions [30]. The adoption of drone technology in agriculture is transforming traditional farming methods, increasing efficiency, and encouraging sustainable resource use. Drones are used in various innovative ways, such as crop spraying, where they evenly distribute pesticides, fertilizers, and herbicides across fields. This approach not only reduces labor costs but also minimizes farmers' exposure to hazardous chemicals [31]. Crop health monitoring, which utilizes high-resolution cameras and artificial intelligence, detects early signs of diseases, pest infestations, and water stress. For example, in cashew farming, AI-driven drones have achieved up to 95% accuracy in identifying anthracnose disease in leaves, enabling timely treatment and decreasing crop loss [32]. Drones in India are also assisting with seed planting, especially in areas that are hard to reach or have difficult terrain [33]. Along with the current application of drones in agriculture, the Indian government has launched several initiatives to promote and regulate drone use. Key programs and regulations include the following. 2.3.1. Digital Sky Platform Launched by the Directorate General of Civil Aviation (DGCA), the Digital Sky Platform is a single-window online system for drone registration and approval processes in India. It offers an interactive airspace map that categorizes regions into green, yellow, and red zones to assist drone operations. Operators can register their drones, apply for necessary permissions, and obtain Remote Pilot Certificates through this platform [34]. 2.3.2. Kisan Drones The "Kisan Drones" program was launched to modernize the agriculture industry and promote the use of drones for various farming tasks. These drones assist with activities like assessing crops and digitizing land records by applying fertilizers and insecticides. The program aims to advance precision agriculture, reduce labor costs, and improve efficiency [35]. 2.4. Rules and Regulations Every

country has laws and regulations about flying drones in specific areas to prevent damage and collisions with property, and these laws differ from country to country. India also has laws and policies that govern drones. According to these policies, the regulatory

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authority, the Directorate General of Civil Aviation (DGCA), has classified drones into five main types, which are listed in Table 2 [36]. Table 2. Drone classification in India by weight.

Sr.

Types of Drones

Weights

1 2 3 4 5

Nano drones Micro drones Small drones Medium drones Large drones

Weighing up to 250 g Weighing 0.25 kg to 2 kg Weighing 2 kg to 25 kg Weighing 25 kg to 150 kg Weighing more than 150 kg

Based on the above classification, drone policies are regulated. India first implemented its policy in 2018. According to this policy, the rules and regulations for drones are outlined as follows. 2.4.1. Old Policy 2018 a.

Pre-Flight Requirement

•

Drones larger than the Nano category require a Unique Identification Number (UIN) from the aviation regulator, as shown in Table 3;

Table 3. Requirements for drone flying under the old Indian policy.

Category

Unique Identification Number (UIN)

Operator Permits

Estimated Approval Time

Height Allowed to Fly

Local Police Permission

Flight Plan and ADC

Nano drones Microdrones Small drones and above

No Yes Yes

Yes Yes Yes

Not Required 2–7 days 2–7 days

50 feet 200 feet 200–400 feet

Yes Yes Yes

No No Yes

• •

Like vehicle registration, UIN incurred a fee of INR 1000 and was not issued to foreign entities; Operators of larger drones needed a Unique Air Operator permit (UAOP), like a driver’s license, costing INR 25,000 with a validity of five years [37].

b.

Flying Conditions

•

All drones, except Nano ones, were subject to mandatory equipment requirements, including GPS, anti-collision lights, ID plates, RFID, and SIM facilities; Software ensuring ‘no-permission, no takeoff’ was mandatory; Operators of small or larger drones need to file a flight plan and inform local police; Micro drones required a flight plan only in controlled airspace, while all operators were required to inform local police; Nano drones operated freely, restricted to 50 ft above ground in uncontrolled airspaces and enclosed premises [38].

• • • • c.

Training Requirements

•

Operators requiring a UAOP underwent a five-day training program covering regulations, flight principles, air traffic control procedures, weather, emergency handling, etc.

d.

Constraints

•

Drones were to fly within visual line of sight (VLOS) during the daytime;

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•

Photography using drones was permitted in well-lit enclosed premises with mandatory police notification.

e.

No-Fly Zones

•

DGCA designated 12 categories of “no-drone zones,” including a 5 km radius around high-traffic airports and 25 km from international borders [39]; Additional no-fly zones included areas around strategic locations, state secretariat complexes, moving vehicles, ships, and aircraft.

•

The old policy involved many extra fees, a lot of paperwork, and numerous permissions to obtain. To address this issue and make drone flights easier and more accessible to everyone, a new policy was introduced in 2021. 2.4.2. New Policy 2021 There were some shortcomings in the previous policy (2018). Since new developments happen each year in drone technology, policies and laws need regular updates to keep up. India revised its policy and introduced a new one in 2021. The key changes are listed below.

• • • • • • • • • •

Unmanned aircraft systems, including drones, can operate independently without human intervention; Before 2021, updated drone regulations required 25 separate submissions and a potential 72-step approval process, which has now been simplified to 5 forms and 4 stages; All previously issued authorizations, including unique identification numbers and certificates, have been revoked; Drone registration fees, previously based on size, have been standardized to INR 100 regardless of drone size [40]; The required number of approvals dropped from 72 to just 4, and the number of forms went down from 25 to 5; The Civil Aviation Ministry is deploying a digital sky platform for centralized approvals that can be accessed on mobile devices; Drone flying zones are divided into yellow, green, and red areas, with reduced boundaries for flights near airports; Security clearances are no longer required for licensing and foreign ownership of drones; Companies are now allowed to be regulated by the Director General of Foreign Trade; The weight limit for permitted drones increased from 300 to 500 kg.

Moreover, the 2021 Drone Rules greatly reduced the regulatory and financial hurdles for drone adoption in Indian agriculture. With easier licensing procedures and the launch of the Digital Sky Platform, small and marginal farmers now find it simpler to legally access drone services [41,42]. Government initiatives like the Sub-Mission on Agricultural Mechanization (SMAM) provide subsidies ranging from 40% to 100% for buying

drones, especially helping farmer producer organizations (FPOs) and self-help groups (SHGs). These changes have increased farm efficiency, cut input costs by up to 50%, and boosted yields by 15–25%. The policy has also promoted rural entrepreneurship through drone training programs, notably empowering women with initiatives such as NAMO Drone Didi [43]. 2.5. Drone Adoption Trends Among Small-Scale vs. Large-Scale Farmers in India Due to factors such as awareness, financial capability, and the extent of application, there are clear differences in how small- and large-scale farmers in India adopt drone technology.

A significant portion of small-scale farmers (73.33%) are becoming aware of the potential benefits of drone technology. Additionally, 61.67% of those who knew about drone technology reported using it in their farming activities, particularly for crop spraying. However, the high initial costs and technical complexities of operating drones present major barriers to wider adoption among this group. To address these challenges, initiatives such as Custom Hiring Centres (CHCs) have been established to provide drone rental services, making the technology more accessible and affordable [44]. Large-scale farmers, on the other hand, have higher drone adoption rates primarily because of their greater financial resources and ability to invest in advanced technologies. These farmers utilize drones not only for crop spraying but also for vegetation control, disease detection, and soil monitoring. Regional states such as Punjab, Haryana, Andhra Pradesh, and Tamil Nadu are leading in adopting drone technology [45]. Their capacity to purchase and operate drones allows them to increase productivity and improve efficiency across large farming areas. To further illustrate the regional landscape of agricultural drone usage in India, the following Table 4 provides a comparative overview of drone adoption across various Indian states. It categorizes states based on their primary crops, policy support, market engagement, and overall adoption levels. Table 4. Regional trends in agricultural drone adoption across Indian states. Indian State

Key Crops and Focus Areas

Notable Initiatives and Features

Drone Adoption Level

Ref.

Telangana

Paddy, cotton, pulses

Major pilot projects, research hubs, and 90% of national SOPs

Very high

[46]

Maharashtra

Sugarcane, cotton, horticulture

‘Namo Drone Didi’ scheme, rural SHG outreach, startup partnerships

Very high

[47]

Andhra Pradesh

Paddy, cotton, horticulture

Large-scale distribution to CHCs, early adopters

High

[48,49]

Punjab

Rice, wheat, sugarcane

Precision spraying, partnerships with manufacturers and FPOs

High

[50]

Haryana

Rice, wheat, sugarcane

Government incentives, precision spraying

High

[51]

Tamil Nadu

Rice, cotton

State-run programs, SOP contributions, research support

High

[52]

Uttar Pradesh

Sugarcane, wheat

Custom hiring centers, rising adoption in major crop belts

High

[53]

Madhya Pradesh

Wheat, soybean

Government projects, CHC-based adoption

Moderate-High

[54]

Karnataka

Ragi, maize, horticulture

State collaboration with manufacturers, farmer training

Moderate

[55]

Gujarat

Cotton, groundnut, horticulture

State pilot projects, growing private sector involvement

Moderate

[49,56]

Odisha

Paddy, pulses, horticulture

Bank loan support, pilot projects

Moderate

[57]

Rajasthan

Wheat, mustard, pulses

Kisan Drone centers, government subsidies

Moderate

[58]

Kerala

Spices, rubber, coconut

Pilot projects, limited but growing adoption

Low-Moderate

[59,60]

Chhattisgarh

Rice, pulses

Government-supported demonstrations, CHCs

Low-Moderate

[61,62]

Bihar

Rice, wheat, maize

Emerging adoption, government pilot programs

Low-Moderate

[63,64]

Uttarakhand

Wheat, rice, fruits

Demonstrations, training programs

Low

[65]

West Bengal

Rice, jute, vegetables

Pilot projects, limited drone use

Low

[66]

Rice, tea, horticulture

Early-stage, sporadic pilots, limited infrastructure

Very low

[67]

Assam and NE States

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The table above highlights both the current situation and regional differences in agricultural drone use across India. Southern and western states, with stronger policies, institutions, and financial resources, are leading in adoption. Meanwhile, eastern and northeastern states continue to fall behind due to infrastructure issues, lower incomes, and fragmented landholdings. However, drone usage in India is expected to grow significantly in the future. The Indian drone market forecasts an 80% compound annual growth rate (CAGR) from 2020 to 2025 [68]. This growth will likely boost adoption rates in the regions that are currently lagging.

- Methodology To conduct a comprehensive literature review, as shown in Table 5, on the adoption of drones in Indian agriculture, Google Scholar was chosen as the main database for sourcing relevant research papers. It offers access to a wide range of peer-reviewed journal articles, conference proceedings, and technical reports from reputable sources such as IEEE Xplore, Springer, and other academic repositories.

Additionally, online news articles, government publications and reports, blog posts, and annual market reports were analyzed to gain real-world insights into adoption trends, policy developments, and market dynamics. Table 5. Literature review criteria.

Aspects	Details
Database	Google Scholar
Time Range	2018–2025 (last 8 years)
Search Keywords	Drones in Indian agriculture, Agricultural drone technology India, Regulatory challenges for agricultural drones in India, Economic impact of drone adoption in Indian farming Precision agriculture using drones in India, Small-scale farmers and drone adoption in India
Inclusion Criteria	-Peer-reviewed journal articles -Conference proceedings -Government reports -Focus on the Indian agricultural sector
Selection Process	-Title and abstract screening -Full-text review -Thematic categorization
Thematic Categories	-Technological advancements -Economic feasibility -Policy challenges -Adoption barriers for small-scale farmers
Limitations	-Access to paywalled content -Manual verification of source credibility

A total of 366 sources were collected and organized using Zotero, a reference management tool. Among these, the distribution of document types was: 176 journal articles, 25 blog posts, 99 news articles from websites, 21 conference papers, and 6 book sections. These diverse references enabled a multidisciplinary understanding of the topic. Ultimately, 237 of these references were cited in the final review. Zotero facilitated efficient thematic tagging and classification of sources, which helped structure the literature around key themes. The literature search was conducted using a combination of keywords and Boolean operators. The main search queries included terms such as “Drones in Indian agriculture,” “Agricultural drone technology India,” “Regulatory challenges for agricultural drones in India,”

“Economic impact of drone adoption in Indian farming,” “Precision agriculture using drones in India,” and “Small-scale farmers and drone adoption in India.” Additional filters were applied to ensure relevance, including a publication year restriction to the last eight years (2018–2025). This ensured that only recent progress and emerging challenges in the field were considered. Furthermore, only peer-reviewed journal articles, conference proceedings, and government reports were selected to ensure the reliability and credibility of the reviewed literature. Studies focusing on global drone applications were excluded unless they provided specific comparative insights relevant to India’s context. The paper selection process consisted of several stages. First, titles and abstracts of the search results were screened to remove studies that were not directly related to the research scope. The remaining documents then underwent a full-text review, during which key insights were extracted, focusing on economic feasibility, regulatory challenges, and technological progress. To enable organized analysis, the chosen papers and sources were grouped into four thematic categories.

• • • •

Technological advancements (97 sources); Economic feasibility (53 sources); Policy challenges (41 sources); Adoption barriers for small-scale farmers (46 sources).

This thematic framework enabled a systematic understanding of the factors influencing drone adoption in India's agricultural sector. Despite the thorough and comprehensive approach, some limitations were encountered. Restricted access to paywalled content prevented the inclusion of certain valuable studies. Additionally, while Google Scholar indexes many documents, it also includes non-peer-reviewed sources. As a result, manual verification of each source's credibility was performed to maintain the review's integrity.

- Indian Agricultural Drone Landscape The use of drones in India is growing. Drones are becoming more important in Indian agriculture for several reasons. Some of these are listed below. 4.1. Precision Farming More than half of India's workforce is employed in agriculture and related sectors, making it the second most populous country in the world. Despite having the secondlargest crop production and the most fertile land globally, it falls behind in expanding its share of the economy. Innovative and advanced technologies are needed to address these issues. Here, precision farming provides farmers with many opportunities to cultivate higher-yielding crops suited to specific areas. Precision agriculture enables farmers to use inputs such as water, fertilizers, and pesticides more efficiently, reducing waste and environmental impact [69]. Modern farming techniques and AI present promising solutions for precision agriculture. Technologies like precision farming, biotechnology, genetics, and drones are just a few examples that can enhance sustainability, productivity, and efficiency. Drones equipped with advanced sensors and imaging systems allow farmers to monitor crop health, soil conditions, and irrigation needs in real time [70,71]. Although precision agriculture is a vital part of farming, it remains an advanced and costly technology that works very efficiently, which is a major obstacle to its wider affordability and adoption in developing countries like India [72]. 4.2. Shortage of Labor The agricultural industry in India faces challenges due to limited labor availability because of its heavy reliance on manual work for tasks such as plowing, sowing, and harvesting.

Although manual labor has been a core part of Indian farming for generations, it can still be physically demanding and time-consuming, which limits the scale and efficiency of farming operations. The decline in agricultural labor is a complex issue caused by various factors, including migration from rural areas to cities, decreasing interest among young people in farming careers, insufficient access to advanced farming technologies, and the division of farmland ownership [73]. Agricultural work is seasonal, meaning jobs are available only for a few months each year. This prompts workers to seek more stable employment in other fields, such as electrician and plumbing roles. Furthermore, the agricultural workforce continues to shrink because of migration to nearby urban areas in pursuit of better educational and job opportunities. The shortage of workers is also worsened by international migration for overseas job prospects. Additionally, government programs like the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA) [18], intended to support rural workers, unintentionally increase labor costs for farmers, aggravating the worker shortage. The lower social status associated with agricultural jobs discourages many people from choosing careers in this field. Therefore, drones can play a vital role in addressing labor shortages. They can perform tasks such as crop monitoring and pesticide application more efficiently, reducing dependence on manual labor [74]. 4.3. Time Saving Drones provide significant time savings for Indian agriculture. They can spray fertilizers, pesticides, and other crop protection products much faster than traditional methods [75,76]. Conventional farming practices in India often rely on limited modern technology. For example, the continued use of backpack spray pumps is outdated and inefficient, as they are labor-intensive and offer limited coverage compared to modern alternatives like tractor-mounted sprayers and drones. A farmer using a backpack spray pump to apply pesticides across a large field, as shown in Figure 3, may spend hours manually covering the area, which leads to inefficiency in time and labor [48]. This method also poses health risks to farmers due to direct exposure to chemicals. In contrast, a farmer using a tractor-mounted sprayer or drone can complete the task much faster with more precision, reducing labor needs and health hazards while ensuring even application and increasing productivity.

Figure 3. The farmer is using the traditional spraying method [77].

4.4. Effective for Pesticide Spraying The excessive use of pesticides and fertilizers in Indian agriculture has raised concerns due to their negative effects on the environment, soil health, and human well-being [78]. Overapplication of these chemicals can cause water pollution, reduce biodiversity, lead to soil erosion, and pose health risks to farmers and consumers [79]. According to the Department of Agriculture and Farmer Welfare, India ranks among the top global producers and consumers of pesticides, with Uttar Pradesh and Maharashtra as the leading states for pesticide use. Multiple research reports from 2011 to 2020 have linked the presence of 45 different types of cancer among rural farmers in India to pesticide exposure [80]. Dronebased pesticide spraying greatly minimizes farmers' risk of pesticide exposure. Research indicates that drone operators face lower risks of dermatitis, asthma, and chronic bronchitis compared to ground-based sprayers [81]. Moreover, drones use substantially less water for pesticide application—while traditional methods may require over 100 L, drones typically use only 5 to 6 L, an essential benefit in water-scarce areas. Using drones for pesticide application has also been shown to boost crop yields. For instance, a study in Haryana's Kurukshetra District reported a 6.25% increase in yield and a 2.25% enhancement in crop quality [82]. 4.5. Less Water Usage Drones are increasingly important for reducing water use in Indian agriculture, promoting more sustainable and efficient farming. It is important to note that water depletion remains a major challenge due to factors like groundwater over-extraction, inefficient irrigation, and climate change. Many regions experience water scarcity (Figure 4), impacting crop yields and farmers' livelihoods. The excessive extraction of groundwater for irrigation, combined with poor water management practices, has caused a rapid decline in water tables nationwide. Climate change worsens this problem by causing unpredictable rainfall and extended droughts in many areas.

Figure 4. Water stress levels across Indian states, categorized from extremely high (>80%) to low (<10%) [83].

As a result, farmers encounter difficulties in securing water for their crops, leading to reduced agricultural output and economic struggles. Most irrigation relies on the overuse of groundwater in Punjab, Haryana, and Western Uttar Pradesh regions [84]. According to the Central Ground Water Authority's 2020 Ground Water Estimation report, Punjab now extracts the highest amount of groundwater in the country. Irrigation uses up 97% of groundwater. Paddy is mainly cultivated through irrigation. Agriculture in Punjab is centered around paddy crops. The Punjab Agriculture Department reports that out of

the total 3.59 million hectares, 3.13 million hectares were cultivated with paddy during the 2022–2023 kharif season [85]. Since excessive water use is a major issue for Indian farmers, drones play a critical role in addressing this challenge. Drones equipped with advanced sensors and imaging technology allow farmers to monitor soil moisture and crop health in real time. This facilitates targeted irrigation, ensuring water is applied only where and when needed, which greatly reduces overall water use. Currently, various water-saving methods such as mulching, crop rotation, and soil moisture management can be employed. When combined with drone technology, these practices significantly improve water efficiency in agriculture [86]. 4.6. Current Use of Drone Applications in India 4.6.1. Pesticide and Fertilizer Spraying In India, the adoption of drone technology in agriculture has driven significant improvements in crop management practices [87]. Drones are increasingly used for automated spraying of pesticides and fertilizers, effectively reducing health risks associated with manual application and boosting operational efficiency, as shown in Figure 5. The Indian Agriculture Ministry estimates that using a drone with a 10 kg payload costs roughly INR 350–450 per acre, based on six hours of daily operation covering about 30 acres [88]. Field data show that drone spraying provides uniform coverage, even for taller crops like sugarcane and orchards, leading to a 25–30% decrease in pesticide and herbicide use due to precise application. The technology also conserves water significantly, using droplets of around 50 µm compared to the 500 micron droplets in manual spraying, which results in an 80–90% reduction in water consumption. Additionally, drones can spray pesticides over 4000–6000 m2 of farmland in just 10 min, demonstrating their fast application ability [89]. These performance indicators are further supported by pilot studies and field experiments conducted across various Indian states. These studies offer empirical evidence of the operational and economic efficiency of agricultural drones, especially for pesticide application, crop monitoring, and input optimization. Table 6 summarizes key findings from recent drone trials across different crop types and regions in India, highlighting cost savings, labor reductions, and yield impacts.

Table 6. Summary of economic and operational efficiency outcomes from agricultural drone pilot studies in India. Study (Year)

Location

Crop

Drone Applications

Cost Reduction

Yield/Income Impact

Operational Efficiency

Saranya et al., 2024 [90]

Pondicherry (TN)

Paddy

Fertilizer/pesticide spraying

6.04% per acre

Net income: INR 22,960 vs. INR 15,931 (non-drone)

Uniform spraying, improved input optimization

Y. A et al., 2024 [91]

Thanjavur and Madurai (TN)

Paddy

Precision input, crop monitoring

~17.5% total

Yield: 2032 vs. 1955 kg; net profit: + INR 7331

Improved application efficiency

Gowri Shankar R et al., 2024 [92]

Trichy and Pudukkottai (TN)

Paddy

Crop health monitoring, pesticide application

30% (cultivation); 12% (total)

Profit + INR 4355/acre; 41% income rise

Precision monitoring, targeted interventions

Dhivya C et al., 2024 [93]

Coimbatore (TN)

General Agriculture

Crop monitoring, resource management

Qualitative only

Yields optimized (no % data)

Optimized input application

Farheen Noor & Noel, 2023 [82]

Kurukshetra (HR)

Paddy

Pesticide spraying, health monitoring

Irrigation: 106.5 → 12.25; Labor: 200 → 50

Yield +6.25%; quality +2.25%

Water use: 5–6 L vs. 100+ L/acre; 5–7 vs. 35 min/acre

Chauhan et al., 2025 [94]

Pune (MH)

Tomato, okra

Decision support, irrigation/fertilizer optimization

Water ↓ 20–30%; fertilizer ↓ 15–25%

Tomato: +15–25%; okra: +10–20%; BCR: 2.5–3.0

High-res mapping; 80–85% pest/disease detection

Yallappa et al., 2017 [95]

Karnataka

Groundnut, paddy

Sprayer dev. and pesticide application

Spraying cost: INR 345–367/ha

N/A

Coverage: 1.08 ha/h; increased droplet uniformity

Note: Arrows (↑/↓) indicate increase or decrease, respectively, in the mentioned parameter. For example, "Water ↓ 20–30%" denotes a reduction of 20–30% in water usage.

4.6.2. Crop Health Monitoring Crop health monitoring with drones is rapidly growing in Indian agriculture, providing many advantages to farmers and the agricultural industry. Drones fitted with multispectral cameras, including near-infrared (NIR) and red-edge bands, allow for the calculation of vegetation indices like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI).

Figure 5. Pesticide spraying (retrieved from Wang et al. [96]).

These indices offer valuable insights into plant health, chlorophyll levels, and water stress, enabling more precise and timely intervention [97]. There are various examples of practical crop monitoring using UAVs. Adhao Asmita Sarangdhar and colleagues developed a system using UAVs to identify and manage diseases affecting cotton leaves. This system also tracks soil quality by connecting sensors to a Raspberry Pi, providing important data on moisture and other soil factors that influence crop growth [98]. Mohamed Kerkech et al. focused on detecting a specific disease (ESCA) affecting grapevines using UAV imagery and convolutional neural networks (CNNs). The UAV images were processed to classify the health status of the grapevines and create a disease map showing the potential for accurate crop monitoring and management [99]. Duana et al. used drones to monitor wheat growth with NDVI techniques. The UAV captured images using a multispectral camera and calculated NDVI values at different growth stages, which helped assess the health of the wheat crop and relate it to yield outcomes [100,101]. 4.6.3. Irrigation Management The adoption of drone technology for irrigation is part of a broader trend in Indian agriculture toward more sustainable and efficient water management practices. This technology is likely to be used in areas where water conservation is a priority and where farmers have access to the necessary resources and support for implementing advanced agricultural technologies. As India faces increasing water scarcity due to climate change, drones are being used to adapt irrigation practices in affected regions. A case study in the Coimbatore District, Tamil Nadu, revealed that farmers have adopted drone technology for various agricultural practices, including irrigation management. Farmers have suggested that crops such as onions, cauliflower, and cabbage could be particularly well-suited for drone-based applications. Owing to their specific structural characteristics and growth patterns, these crops may benefit significantly from the precision and efficiency of agricultural drones. The

use of drones for controlled irrigation ensures that crops receive the optimal amount of water, reducing the risk of overapplication, damage, and wastage [74]. Here, we specifically want to highlight the Indian farmers' perceptions of drones. We have reviewed multiple studies across Tamil Nadu, Haryana, and other rural areas in India showing that drones significantly improve operations, especially in tasks like pesticide spraying, crop monitoring, and irrigation management (see Table 7). Farmers report that drones help lower labor and input costs, optimize chemical use, and conserve water resources. For example, Shankar et al. found that drone use resulted in a 30% reduction in costs and a 41% increase in income [92], while Noor and Noel documented a 6.25% rise in crop yield and a 2.25% improvement in crop quality [82]. Awareness of drone applications is also quite high, with one study indicating that 75% of farmers associate drones with spraying, 68% with pest and disease control, and 66% with irrigation by M. P P et al. [102]. Additionally, drones are viewed as promoting sustainable farming practices through more efficient resource use and less environmental impact. However, despite these positive perceptions, several barriers limit widespread adoption. Major obstacles include high initial costs, regulatory uncertainty, skill gaps, and technological challenges. Masih et al. reported that 70% of Indian farmers see cost as a key issue [103]. While the immediate environmental benefits of drones are well recognized, most studies overlook the long-term environmental impacts and issues related to disposing of drone equipment and batteries. Table 7. Summary of recent empirical studies assessing Indian farmers' perceptions, adoption barriers, and application of agricultural drones. Authors (Year)

Sample Size

Region

Drone Applications

Perceived Benefits

Main Barriers

Environmental Issues

Dhivya et al. (2024) [93]

N/A

Coimbatore, Tamil Nadu

Spraying, monitoring, irrigation

Improved efficiency, input optimization, labor saving

Cost, skill gaps, fragmented land, availability

Sustainability concerns

M. P P et al. (2024) [102]

60

Coimbatore, Tamil Nadu

Spraying (75%), pest control (68%), irrigation (66%)

Efficiency, high awareness, sustainability

Weather, maintenance, connectivity, policy, lack of training

Sustainable practices noted

Barathkumar et al. (2024) [104]

120

Coimbatore, Tamil Nadu

Spraying, monitoring, irrigation

Reduced chemical use, improved monitoring, higher yield

Cost, complexity, regulation

Water conservation concerns
Masih et al. (2025) [103]
40 (interview), 100 (survey)
India and Netherlands
Early pest detection, resource management
Sustainability noted by 60% (India)
Cost (70%), socio-cultural and policy barriers
Sustainability highlighted
Noor & Noel (2023) [82]
90
Kurukshetra, Haryana
Spraying, monitoring, irrigation, soil analysis
Yield ↑6.25%, quality ↑2.25%, labor and water savings
Awareness, cost, smallholder access, need for technical support
Manual spraying health issues mentioned
Sundar et al. (2023) [105]
N/A
Multiple districts, Tamil Nadu
Chemical spraying, crop protection
Efficiency, social/economic factors affect adoption
Cost, family influence, and policy barriers
N/A
Shankar et al. (2024) [92]
160 (60 UAV, 100 non-UAV)
Trichy and Pudukkottai, Tamil Nadu
Spraying, monitoring, pest control, irrigation
Cost ↓ 30%, income ↑ 41%, economic efficiency ↑ 90%
Cost, pilot shortage, maintenance, regulation
Mentioned runoff reduction, drift concern
Prabhu et al. (2021) [106]
N/A
India
Weed management, monitoring, resource optimization
Cost-effective, high accuracy (92.6–95.4%)
Training, flight time, small farms, low income
Health protection noted
Sangode (2024) [107]
N/A
India
N/A
N/A

Social anxiety, resistance, regulatory uncertainty, “environmental toll”

Environmental toll (vague)

4.7. India-Based Drone Companies India has experienced significant progress in drone development and adoption over the past few years. Many new drone startups have emerged to create agricultural drones that improve farming efficiency and precision. Numerous drone companies are actively involved in agricultural operations, and Table 8 outlines various Indian-made agricultural

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drones, including their manufacturers and key specifications. However, a few companies stand out in this field, such as Garuda Aerospace, which focuses on pesticide spraying and precision farming. Kisan Drones are equipped with artificial intelligence (AI), machine learning, and GPS sensors to give farmers real-time crop data. Dhaksha Unmanned Systems produces DH series drones known for their efficient spray systems and compatibility with farm management software. Additionally, Thanos Technologies developed the Syena series of agricultural drones, featuring intelligent spraying technology and real-time data monitoring. IdeaForge manufactured the AGRI series drones, recognized for their high payload capacity and advanced spraying systems suitable for large-scale farming [108]. Along with the drone models listed in Table 8, the Indian agricultural drone ecosystem includes a wide range of companies, startups, government agencies, and supporting organizations. These groups are not only developing and deploying drone technologies but also helping with training, market access, and research infrastructure. Table 9 highlights the main stakeholders driving the drone revolution in Indian agriculture. Additionally, the following government and institutional bodies are crucial in promoting drone adoption in Indian agriculture.

• • • • •

Directorate General of Civil Aviation (DGCA): oversees drone operations and certifies training organizations; Indian Council of Agricultural Research (ICAR): leads research projects on drone-based crop monitoring and pest control [109]; State agricultural departments: conduct drone field demonstrations and support subsidies in states such as Gujarat, Himachal Pradesh, and West Bengal; Skill India Mission: creates certified training programs for drone pilots and rural youth [110]; Farmer producer organizations (FPOs): promote drone service adoption and gather demand at the community level.

4.8. Key Statistics and Market Growth of the Indian Drone Market The Indian agricultural drone market has experienced substantial growth, reaching a valuation of USD 243.60 million in 2024. According to projections by the IMARC Group, the market is expected to expand significantly, as shown in Figure 6a, reaching USD 2110.60 million by 2033, with a strong compound annual growth rate (CAGR) of 24.10% during the forecast period (2025–2033). This growth is mainly driven by robust government support, increasing adoption of precision agriculture, severe labor shortages, and ongoing technological advancements. Together, these factors make drone-based solutions more efficient, affordable, and accessible for Indian farmers [111]. In terms of application, field mapping represents the largest segment of drone use in Indian agriculture at 35.4%, followed by variable rate application at 24.6%, crop scouting at 18.2%, and other uses at 21.8%, as illustrated in Figure 6b. The Indian government is promoting the use of drones in agriculture through various schemes and subsidies, such as the Production-Linked Incentive (PLI) scheme, which aims to boost the domestic manufacturing of drones and drone components in India. It was launched in September 2021 and provides financial incentives to companies involved in drone production, encourages investment, and reduces reliance on imports. The scheme allocates INR 120 crores over three financial years to double the combined turnover of all domestic drone manufacturers [112]. In Table 10, some PLI scheme beneficiaries are mentioned as the top drone manufacturers and importers across India. Additionally, government restrictions on foreign drone imports are encouraging domestic production and benefitting initiatives like the Kisan Drones program and state-specific drone policies in Himachal Pradesh, Gujarat, Goa, and West Bengal [113].

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(a)

(b)

Figure 6. (a) Growth projection of India’s agricultural drone market (2024–2033); (b) Indian agriculture drone market share by application (2024). Table 8. Specifications of Indian agricultural drones. Manufacturer

Drone Model

Tank Capacity (L)

Battery Life (min)

Flight Range (km)

Max Speed (m/s)

Ref.

Garuda Nav Krishaak Dhaksha Drones Thanos Prime UAV Labh Group IdeaForge Paras Aerospace Marut Drones

Garuda Kisan Drone NAV KRISHAAK DH-AG-H1 Syena-H10i Prime UAV Labh Drone Q4I Paras Agricopter Agricopter AG 365

10 L 16 L 12 L 10 L 10 L 10 L 10 L 10 L 10 L

19 min 20 min 35 min 20 min 12 min 17 min 40 min 20 min 22 min

1.5 km 10 km 0.5 km 0.5 km 2 km 0.5 km 4 km N/A N/A

10 m/s 10 m/s 5 m/s 10 m/s 8 m/s 10 m/s 7 m/s 4 m/s N/A

[114] [115] [116] [117] [118] [119] [120] [121] [122]

Table 9. Key players and startups in the Indian drone agriculture market. Company/Startup

Location

Key Focus/Contribution

Ref

Garuda Aerospace

Chennai

Precision spraying, crop health monitoring, DGCA-certified training, large-scale farmer outreach

[123,124]

IoTechWorld Avigation

Gurugram

DGCA-approved Agribot drones for spraying, broadcasting, soil/crop health assessment

[125]

Throttle Aerospace

Bangalore

UAVs for land mapping, surveillance, inspection, disaster management in agriculture

[126]

Aarav Unmanned Systems

Bangalore

High-resolution imagery for crop health monitoring and yield estimation

[127]

FlytBase

Pune

Autonomous drone platforms for crop monitoring, data collection, smart farming solutions

[128]

Marut Drones

Hyderabad

Multi-utility agri drones, pesticide spraying, direct seeding, drone operator training

[129]

BharatRohan

Delhi, Lucknow, Hyderabad

Drone-based hyperspectral imaging, precision agri-advisory, FPO partnerships, traceability platforms

[130]

FlyLab Solutions

Nashik

DroneDekho platform, precision farming, micro-entrepreneur empowerment, water conservation

[131]

Vyomik Drones

Hyderabad

Crop spraying, field mapping, health analysis, fertility monitoring

[132]

Dhaksha Unmanned Systems

Chennai

Agricultural drones, drone services, technology solutions

[133]

The agricultural drone industry is seeing major investments, with startups focusing on creating drone solutions customized for farming. The Indian fintech market, which includes AgriTech, is valued at USD 31 billion and is projected to reach USD 84 billion by 2025, growing at a CAGR of 22% [134]. Companies like Marut Drones, Bharat Rohan, AVPL International, and Dhaksha Unmanned Systems are attracting funding to manufacture drones and offer drone-based services. Indian investors are showing interest in the drone-as-a-service business model because the average farm size in India is about five acres, making it well-suited for drone technology, especially for surveying, crop health monitoring, and precision spraying. This also lets farmers rent drones for various other agricultural tasks. For example, investors such as Lok Capital see potential in the agricultural drone sector but admit that real progress might take 5–7 years [135]. However, since the market is still in its early stages, time is needed for farmer education and adoption. That there are several notable partnerships and government funding initiatives supporting drone development in India's agricultural sector [136]. The Kisan Drone scheme provides grants covering up to 100% of the cost of an agricultural drone (maximum INR 10 lakhs) for various agricultural institutions [137]. Additionally, the government offers a 50% subsidy (up to INR 5 lakhs) for agriculture graduates establishing custom hiring centers (CHCs), and farmers' producer organizations (FPOs) can receive up to a 75% subsidy on drone costs for demonstration purposes. The Drone Didi Program (DDP), launched in 2023 to train women in acquiring and piloting drones, now supports 15,000 women's self-help groups with financial assistance and loans for drone purchases [138]. Moreover, international collaborations like the India–Japan partnership help improve drone hardware manufacturing, R&D, and testing infrastructure, supporting sustainable market growth [139]. Recent advancements in agricultural drone technology have resulted in major industry collaborations to modernize farming practices in India. One key initiative is the partnership between Thanos Technologies and the Indian Farmers Fertilizer Cooperative, Ltd. (IFFCO), established through a memorandum of agreement (MoA). This collaboration aims to deploy over 500 drones for aerial fertilizer spraying, covering about 1 million acres of farmland across multiple states, including Telangana, Andhra Pradesh, Gujarat, Madhya Pradesh, and Tamil

Nadu [140]. 4.9. Success Stories in Indian Farms Multiple case studies have been conducted on Indian farms that have benefited from drone technology. In Punjab, farmers use drones for efficient pest control in cotton fields, resulting in less pesticide use and higher yields. Similarly, in Maharashtra's vineyards, drones are used to spray fungicides, ensuring even coverage and lowering labor costs [141]. Darubrahma Automation Robotics, a startup founded by Rajendra Kumar Das, has revolutionized agriculture across multiple states in India. Since its inception, their drones have covered over 30,000 acres of farmland in states like Odisha [142]. In Tamil Nadu, farmers have adopted drones for spraying, sowing, and various agricultural activities. The state is known as the birthplace of precision agricultural drones, with farmers leading the way in adopting this technology. According to Agnishwar Jayaprakash, founder and CEO of Garuda Aerospace Pvt. Ltd., these drones have boosted productivity by 30% while reducing fertilizer, pesticide, and water costs by 70% [143].

Table 10. Drone manufacturers are beneficiaries of the PLI scheme. Year Established

Types of Drones

Key Models

Technical Specifications (Flight Range & Duration, Weight)

Technology Used

Primary Market

Revenue (2023)

2007

Surveillance, Mapping, Homeland Security, Agriculture

Q6 UAS, Q4i UAS, NETRA V3 + UAS

15 km & 120 min, Target Tracking

5G Technology, Live Streaming

Civil & Defence sector

Raphe Mohib

Noida, Uttar Pradesh

2017

Surveillance drones, Logistic drones

MR-20, MR-10

20 kg Payload

Collective Intelligence, Ultra-Light Carbon Fiber Composites

3

AEREO (Aarav Unmanned Systems)

Bengaluru, Karnataka

2013

Surveillance & Land mapping

Aereo—ZFR, Aereo—INP

400 feet, 40 min, 13 kg payload

4

Throttle Aerospace Systems

Bengaluru, Karnataka

2016

Delivery, Enterprise, Cargo
DOPO, TALV-TACT, NIMBLE-1
5
Sagar Defence Engineering
Pune, Maharashtra
2015
Search & Rescue, Inspection & tracking
Spectre M, Spectre P
Sr. No
Company
Headquarters
Idea Forge
Mumbai, Maharashtra
2
1
6
Roter Precision Instruments
Roorkee, Uttarakhand
1936
Surveying & security
Trinity F90+, Roter RC-08
Funding
Certifications
Ref.
INR 1860.1 million
330 cr.
DGCA & Bureau of Indian Standards (BIS) Certified
[144]
Defense
270 cr.
132.55 cr.
DGCA Certified
[145,146]
GIS (Geographic Information System)
Fields & Mining
N\A
15 million
DGCA Certified
[147,148]
5 km, 55 min, 10 kg Payload
multispectral sensors, AES 256-bit encryption used

Defence & land survey

50 cr.

N\A

DGCA Certified, WPC Approved

[149,150]

20 km, 5 kg payload, 60 min

IR (Infrared Camera), cloud connectivity

Defense & military tech

1.67 million

3.3 million

DGCA Certified

[151,152]

7.5 km, 90 min, 5.3 kg payload

Anti-collision Strobe and Position Lights, Lidar, and advanced RGB Sensors

Area mapping

N\A

N\A

N\A

[153]

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A study conducted in the Virudhunagar district of Tamil Nadu examined 60 farmers, including 30 drone users. The results showed that drones offer digital, informative, and accurate field management for crops like rice, cotton, and corn [154].

- Issues and Challenges Indian agriculture has great potential for improvement through drone technology, which can boost efficiency and traditional farming methods. According to Price Water Coopers (PwC) research, the infrastructure sector in India holds the highest potential value for drone-powered solutions at USD 45.2 billion [155]. However, the widespread adoption of drones in farming faces significant challenges, such as the following. 5.1. Technological Challenges 5.1.1. Hardware Limitations Low-cost hardware remains a major limitation for Indian drones. One of the main issues faced by UAVs is their limited operational time, mainly due to battery constraints. Drones typically fly for 20–60 min because they carry heavier loads [156]. This restricts ground coverage per battery charge and increases operational costs. Enlarging the battery is not practical, as it would impact the drone's weight and maneuverability [157]. Additionally, the limited payload capacity of agricultural drones can reduce the effectiveness of pesticides and fertilizers during field spraying. With limited capacity, drones may not carry enough chemicals to cover large areas efficiently, leading to incomplete coverage and diminished spraying effectiveness [158]. A lower payload capacity often means more frequent refills, interruptions in spraying, and higher overall time and resource use. Furthermore, limited payload capacity also restricts the amount of equipment and sensors that can be transported during operations, which can limit the variety and quality of data collected, thereby affecting the overall efficiency and effectiveness of drones in agricultural tasks. However, with limited payload capacity, drones might struggle to carry vital equipment such as high-resolution cameras, multispectral sensors, or extra batteries needed for longer flights. This can hinder the drone's ability to gather detailed and accurate information, which is essential for decision-making in farming practices. Researchers are developing advanced algorithms for drones so they can select shorter paths to cover large areas more efficiently. For example, a study discussed the use of a smart algorithm called adaptive multi-start simulated annealing (AMS-SA) to plan optimal routes for drones during flight. Tests show that this algorithm

outperforms existing ones and highlight the benefits of using multi-compartment drones, combining trucks and drones, swapping drone batteries, and considering how package load impacts battery usage [159]. 5.1.2. Import Dependencies Most drone components, such as airframes, propellers, power sources (batteries/engines), and sensors, are imported from countries including China, Europe, and the USA [160]. – – –

Approximately 25% of airframes are imported; Propellers have a 75% import rate; Power plants/batteries/engines also see about 75% of their components imported.

Notably, around 75% of electronic speed controls, servos, and sensor payloads (including DSLR cameras, lidar, and thermal sensors) are imported. This heavy reliance on imports impacts the domestic manufacturing ecosystem and the overall indigenization of the drone supply chain in India.

5.1.3. Data Collection Achieving high accuracy in data collection remains a challenge because accurate data depend on high-quality sensors. Since India mostly imports drone components, including sensors, from other countries, procurement costs stay high, increasing overall expenses for drone manufacturers and end-users. Additionally, proper infrastructure is essential for storing data. During flight, drones produce large amounts of data through sensors and imaging technologies. Analyzing and interpreting this data requires specialized knowledge and tools. Integrating drone data with existing farm management practices and decisionmaking processes can be difficult without adequate infrastructure and support systems. Raw drone data are meaningless without analysis. Drones use various sensors (RGB, multispectral, and thermal) to collect data in different formats. Compatibility issues arise when integrating data from different sources. Farmers struggle to find software that can handle diverse data types and integrate smoothly with existing systems [161]. 5.1.4. Lack of Training Infrastructure Despite growing interest in drone technology and various government initiatives, the lack of accessible and comprehensive training programs remains a major obstacle for Indian farmers, especially small and marginal farmers in rural areas [162]. Most organized drone training courses are located in urban centers, making them geographically inaccessible to rural communities. Additionally, awareness about drone technology and training options is limited. Even when such programs are available, many farmers face barriers due to low digital literacy and limited exposure to advanced technologies. A shortage of certified instructors and DGCA-accredited training centers further limits the reach and quality of drone education in remote areas. Furthermore, training materials are often not available in local languages, which hinders participation by non-English-speaking farmers [163]. Practical, hands-on sessions are also limited, with many programs mainly focusing on theoretical or simulator-based instruction. High costs, travel requirements, and the opportunity cost of leaving farms for training further discourage smallholder participation. These limitations not only slow adoption rates but also increase the risks of improper drone use and missed opportunities for agricultural productivity improvements. 5.1.5. Charging Infrastructure Constraints A major yet underexplored barrier to drone adoption in Indian agriculture is the lack of dedicated charging infrastructure in rural areas [164]. Most villages do not have established drone charging stations, and existing solutions are mostly in the experimental or pilot phase. In regions where drone use is growing, unreliable electricity supply in rural areas further limits the feasibility of consistent drone operation, especially since frequent battery recharging is needed during field tasks. Although solar-powered and renewable energy-powered charging stations have been proposed and tested in limited pilot programs, scaling up faces challenges due to high installation costs, limited energy storage capacity, and reliance on favorable weather conditions [165]. To better understand the economic feasibility of deploying such infrastructure in India's rural areas, Table 11 summarizes the estimated equipment and installation costs for different types of drones and comparable EV charging stations, based on available data and similar EV infrastructure costs.

Table 11. Estimated installation costs for drone charging infrastructure in India. Type of Charging Station

Description

Estimated Equipment Cost (INR)

Estimated Installation Cost (INR)

Total Estimated Cost Range (INR)

Notes

Ref.

Basic Drone Battery Charging Hub

Small-scale battery chargers for drones (non-autonomous)

INR 1200–INR 9000

INR 10,000– INR 30,000

INR 11,200– INR 39,000

Suitable for small drone fleets, limited automation, and rural deployment

[166]

Autonomous Drone Docking Station

Weatherproof, automated drone docks (e.g., DJI Dock 2, M30)

INR 10,00,000– INR 25,00,000

INR 200,000– INR 500,000

INR 12,00,000– INR 30,00,000

High-end solution for continuous drone operations; requires stable power and connectivity

[167]

Solar-Powered Charging Station

Drone charging stations integrated with solar panels

INR 300,000– INR 800,000

INR 100,000– INR 300,000

INR 400,000– INR 11,00,000

Off-grid rural solution; cost varies with solar panel capacity and battery storage

[168]

EV Level 1 AC Charging Station

Slow charging, basic EV charger (analogous to drone charging)

INR 10,000– INR 20,000

INR 30,000– INR 50,000

INR 40,000– INR 70,000

Indicative of low-power drone charging setups

[169,170]

EV Level 2 AC Charging Station

Faster AC charging for EVs

INR 50,000– INR 100,000

INR 50,000– INR 2,00,000

INR 100,000– INR 300,000

Comparable to more robust drone charging hubs

[169,171]

EV DC Fast Charging Station

Rapid charging for EVs

INR 200,000– INR 500,000

INR 600,000– INR 13,00,000

INR 800,000– INR 18,00,000

High power, fast charging; upper bound for drone charging infrastructure

[172]

As shown in Table 11, the cost of establishing drone charging stations in India varies significantly based on the system's type and complexity. While basic battery hubs can be set up for less than INR 40,000, autonomous drone docking stations may cost over INR 30 lakh. Solar-powered stations offer a promising off-grid option for rural areas but are still cost-prohibitive for small-scale farmers due to high initial expenses and weather dependency [173,174]. Additionally, many components (e.g., batteries, solar panels, and inverters) are imported, which increases costs and logistical challenges [175]. Without targeted subsidies or rural deployment models, this infrastructure gap remains a major obstacle to the widespread adoption of drones in Indian agriculture. 5.2. Environmental Constraints India's diverse climate and terrain, ranging from the arid deserts of Rajasthan to the lush forests of the Western Ghats and the towering peaks of the Himalayas, present significant environmental challenges for drone operations [176]. The tropical climate in many parts of India, characterized by high humidity, can affect drone performance and sensor accuracy. Additionally, sudden weather changes are common in tropical regions and can disrupt drone flights and data collection. In some areas, strong winds, rain, and extreme temperatures can hinder drone operation and impact their effectiveness in tasks such as crop monitoring and spraying [177]. For instance, high wind speeds can destabilize drones during flight, affecting data accuracy. Rain can damage sensitive drone components, causing malfunctions. Extreme temperatures can reduce battery life and flight stability, lowering operational efficiency. A study [178] compared drone flyability by analyzing historical weather data—such as wind speed, temperature, and precipitation—against manufacturer thresholds using computer simulations. Weather-resistant drones have considerably higher flyability than standard drones, especially in warm and dry regions. Enhancing weather resistance thresholds for wind speed and precipitation can significantly improve drone flyability, particularly in major population centers. Drone operators must vigilantly monitor weather forecasts and conditions to ensure safe and effective operations. Moreover, many regions covered with dense forests can disrupt drone signals and restrict visibility, making it difficult to gather accurate data and perform surveillance. Areas such as the Himalayas pose extreme challenges for drone operations due to their high altitudes and rugged terrain [179].

5.3. Economic Challenges Cost is a major factor for farmers when considering investment in agricultural drones. The average annual income of a farmer in India is around INR 77,976 (about USD 1000), which limits their ability to invest in new technologies. Although drones have become much more accessible in recent years, there are still significant upfront costs to purchase and operate these devices in agriculture. An entry-level drone meant for small-scale farmers typically costs between INR 50,000 and INR 150,000, while more advanced drones with features like better imaging, longer flight times, and obstacle avoidance can cost up to INR 500,000 or more. This can be prohibitively expensive for many marginal farmers [180]. In addition to the initial purchase, there are ongoing expenses such as repairs, replacement parts, and battery replacements that add to the total cost of ownership. Thus, farmers find it difficult to buy and use drones, especially small and marginal ones, because they have small, fragmented landholdings of less than one hectare, making it hard to justify the cost of drone technology. Lack of government subsidies and financing options is also a factor. Drone adoption requires a large initial investment and raises concerns about future costs, so farmers may hesitate to adopt drones [141]. The second reason relates to funding and investment. Agricultural laborers, who make up a large part of the farming community, have limited access to institutional credit facilities, forcing them to seek loans from non-institutional sources at high interest rates [181]. Despite government initiatives like Kisan Credit Cards (KCCs) and new banking products designed for farmers, many still face difficulties in getting loans due to bureaucratic hurdles, collateral requirements, and limited financial literacy. These barriers make it difficult for small-scale farmers to invest in advanced technologies such as agricultural drones [182]. Third, maintenance costs and training for drone operations further increase the financial burden on many farmers. Investment costs may include the price of drones as well as additional expenses. Furthermore, rapid

advancements in drone technology can require frequent upgrades, adding to the overall investment. The cost of investment (CoI) can be analyzed using the formula: CoI = IAC + TC + MC + UC + RF where

• • • • •

IAC (initial acquisition cost) represents the purchase price of the drone and necessary accessories; TC (training cost) includes expenses related to training personnel for drone operation and data analysis; MC (maintenance cost) covers ongoing costs for drone upkeep, repairs, and software updates; UC (upgrade cost) involves expenses for upgrading drone technology to stay current with advancements; RF (registration fee) involves the mandatory registration fee that drone operators must pay to register their drones with regulatory authorities legally.

These costs emphasize the financial pressure of adopting drones. However, analyzing the economic benefits and return on investment (ROI) helps determine if drone technology is ultimately a profitable choice for farmers. To better understand the ROI and costeffectiveness of drone adoption, we provide a comparison in Table 12 between traditional farming practices and drone-supported operations on a 50 acre medium-sized farm.

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Table 12. Cost–benefit comparison for a medium farm (data adapted from [183]). Conventional Approach

Done-Based Approach

Pesticide Application Labor expense Time needed Chemical usage

Aspect

INR 15,000 per season 5 days 100%

INR 3000 per season (drone operation) 4h 60–70%

Crop Monitoring Labor expense Coverage area Detection precision

INR 8000 per month 20% of field daily 40–60%

INR 15,00 per month (drone surveys) 100% of field in 2 h 80–95%

For pesticide spraying, traditional manual methods cost about INR 15,000 per season in labor and take up to 5 days to finish, often leading to chemical overuse. In comparison, drone-based spraying cuts the operation time to just 4 h and reduces costs to around INR 3000 per season. Moreover, chemical use drops by 30–40% due to more precise application, without affecting the yield. Similarly, for crop monitoring, traditional field scouting costs about INR 8000 per month, covers only around 20% of the field per day, and has detection accuracy between 40 and 60%. Drone surveys, costing INR 1500 per month, can cover 100% of the field within 2 h and achieve detection accuracy of 80–95%, enabling earlier intervention and better decision-making. Based on these operational advantages, the estimated annual savings range from INR 120,000 to INR 180,000 for a 50-acre farm. Factoring in an average drone investment of INR 3–5 lakh (depending on features), the payback period is approximately 2–3 years. These results demonstrate the economic viability of drone adoption for medium-sized farms. For smallholder farmers who cannot afford drone ownership, service-based models such as drone cooperatives, farmer producer organizations (FPOs), and governmentsubsidized operators can provide the same benefits without upfront costs. Financial Outcomes

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Potential annual savings: INR 120,000–INR 180,000 per 50 acre farm Payback period for drone investment: 2–3 years.

5.4. Social Challenges Many rural farmers have a deep-rooted connection to traditional farming practices passed down through generations. They may see the adoption of new technologies, such as drones, as a threat to their existing methods [184]. A lack of awareness and understanding of the benefits of drone technology in agriculture also causes resistance. Farmers might not fully understand the advantages drones provide, leading them to stick with familiar conventional approaches. One reason for this is that there are few training and educational programs available to teach farmers about these technologies. Second, the lack of technical knowledge and training is a significant obstacle to adopting drone technology in Indian agriculture. Operating

drones requires specialized skills that most farmers currently lack due to their age. The shift from traditional farming methods to UAVs will largely depend on the age of farmers, as older farmers are more likely to stick with conventional practices [17]. Flying a drone accurately over fields or crops involves more than just pilot skills; it requires proper training, expertise, and understanding of flight operations and maintenance. Additionally, data analysis and image stitching from drone footage need specialized tools and analytical skills that most marginalized farmers do not possess [185]. In India, especially in rural areas, there is a shortage of trained instructors and courses on drone technology and its agricultural applications. Farmers find it difficult to access the necessary training [186].

- Technological and Policy Solutions and Case Studies Possible solutions that provide social and economic benefits must be implemented to address the problems and challenges discussed in Section 4. To that end, some possible solutions are mentioned. 6.1. Technological Innovations Traditional farming methods are being transformed by next-generation agricultural technologies focused on boosting sustainability, productivity, and efficiency. The use of advanced technologies like artificial intelligence (AI), machine learning (ML), drones, and the Internet of Things (IoT) has revolutionized agriculture. These tools help farmers tackle challenges such as unpredictable weather, resource constraints, and productivity issues [187]. 6.1.1. AI/ML Applications in Drone-Based Agriculture As we enter the AI era, the integration of current devices with AI is growing. In agriculture, artificial intelligence and machine learning (AI and ML) are becoming transformative tools that can significantly boost revenue by reducing losses, enhancing decision-making, optimizing resource use, and managing risks related to agricultural losses [188]. Additionally, several key applications where AI and ML have had a major impact are highlighted. The most important role of AI in agriculture is in crop disease detection. Machine learning algorithms analyze high-resolution images to identify signs of stress, disease, and nutrient deficiencies in plants [189]. Aerial photos taken by drones are used to train machine learning (ML) models with a convolutional neural network (CNN) [190]. These models accurately evaluate plant health and determine whether a crop is affected by disease, enabling AI-driven decision-making to recommend effective mitigation strategies [191]. For example, Mohanty et al. developed a deep learning-based disease detection system that uses the Plant Village dataset to identify 38 different plant diseases with 99.35% accuracy. The system, trained on over 54,000 field images, allows for real-time disease detection through smartphone cameras, drones, and IoT-based monitoring devices. In practical scenarios, if a tomato leaf is infected with late blight, an AI model can detect the disease early and suggest immediate actions [192]. The second-largest use of AI in drones is precision agriculture. Precision agriculture (PA) is a farming management approach that uses information technology and various data forms to optimize farming practices and boost farm efficiency. It involves advanced technologies like sensors, GPS, remote sensing, and data analytics to monitor and control field variability in crops and soil conditions [193]. The main aim of precision agriculture is to help farmers make better decisions about crop management, irrigation, fertilization, and pest control using real-time data [194]. The integration of AI with drones is transforming precision agriculture (PA) by enabling advanced data collection and analysis, which is crucial for understanding real-time field conditions. Using data from drone sensors and satellite images, AI algorithms help farmers continuously monitor their fields to quickly detect pests, diseases, and nutrient deficiencies, allowing for timely actions that protect crop yields [195]. Additionally, AI improves resource efficiency by calculating the ideal amounts of fertilizers, water, and pesticides needed for specific areas, reducing waste and environmental impact. Machine learning-based predictive analytics also enable farmers to forecast crop yields using historical and current drone-collected data, supporting better planning and resource management [196]. Furthermore, AI combines different data sources to give a comprehensive view of agricultural conditions and optimize processes like irrigation. Overall, deploying AI alongside drones in precision agriculture transforms traditional farming into real-time

decision-making systems, promoting higher productivity, sustainable resource use, and improved farming practices [197]. 6.1.2. Integration of the Internet of Things (IoT) with Drones IoT is the most revolutionary technology in modern farming. The basic concept of the Internet of Things in agriculture involves cameras,

sensors, and other smart gadgets that gather data from every farm operation [198]. As IoT-enabled drones are equipped with sensors and high-resolution cameras, they can collect real-time data on crop health indicators, weather conditions, and pest infestation levels [199]. In IoT-driven precision farming, various sensors, such as those for soil moisture, temperature, and humidity, constantly monitor crop growth and environmental conditions, supporting data-driven decisions for better farming outcomes [200]. Several studies have demonstrated the positive impact of IoT integration with drones. A comprehensive review published in early 2025, titled “Harvesting the Future: AI and IoT in Agriculture,” highlighted how integrating IoT with drones has transformed crop management and precision farming. The review stressed that these technologies allow for optimized resource use and increased crop yields through real-time monitoring and data-driven decision-making [201]. Another study focusing on IoT-based precision farming showed that using sensor networks and data collection methods, including drones, allowed for the simultaneous monitoring of soil moisture, temperature, humidity, and crop health [202]. This method has resulted in significant improvements in resource conservation and productivity. A global study published in February 2025 further confirmed these findings, stating that smart farming technologies, including IoT sensors and drones, have greatly contributed to improving agricultural practices, reducing resource waste, and increasing efficiency [203]. The study highlighted that using precision farming techniques and real-time monitoring systems allows farmers to make data-driven decisions about irrigation, fertilization, and pest control, leading to better crop quality and higher yields. Furthermore, IoT-based drones enable automated farm management by sending collected data to cloud platforms, where farmers can view real-time insights through mobile apps [204]. Additionally, 5G-enabled drones improve real-time data processing, supporting swarm drone operations for large-scale farming [205]. Precision agriculture is evolving due to the integration of IoT, drones, and AI, which makes farming smarter, more sustainable, and more efficient. Future advancements in edge computing, blockchain, and machine learning will enhance automated decision-making in agriculture 4.0 [206]. 6.1.3. Solar-Powered Drones for Cost-Efficiency Solar-powered drones, also known as solar-powered unmanned aerial vehicles (SPUAVs), are emerging as a cost-effective and sustainable solution for agricultural use. A major challenge for drones is their limited endurance [207]. Currently, drones mainly run on batteries, which means they must return to the ground often to recharge, typically after only a few hours of operation. Therefore, the next step is to harness solar energy as a sustainable and efficient power source for drones [208]. By using solar energy as their main power source, these drones reduce their dependence on traditional fuels, resulting in lower operational costs and less environmental impact [209]. Integrating solar panels enables SPUAVs to generate electricity, reducing the need for frequent landings and battery replacements. This longer operational time is especially useful for applications like long-duration surveillance, environmental monitoring, and precision agriculture, where continuous data collection is essential [210]. Energy management

strategies (EMS) are vital for controlling the output of solar cells and batteries and efficiently distributing power across various operational stages. Moreover, technological advances in solar cells, rechargeable batteries, and electric motors have progressively improved the efficiency and capabilities of these drones. The extended operating hours and lower energy dependence of solar-powered drones make them very useful for different applications. In agriculture, for example, drones can continually monitor crop health, identify early signs of disease, and improve irrigation and fertilization plans [211]. Additionally, the maintenance costs of solar-powered drones are generally lower. Traditional battery-operated drones need regular battery replacements because lithium-ion batteries deteriorate over time and have a limited number of charge cycles. Solar-powered drones, however, have fewer moving parts and rely less on consumable components, which reduces both the frequency and cost of maintenance. The solar panels are durable and have a long lifespan, often outlasting other drone components [212]. Although the initial investment in solar-powered drones may be higher than that of traditional battery-operated drones, the long-term cost savings can be considerable. A study on solar-powered UAVs for precision agriculture found that these drones could lower operational costs by up to 30% compared to conventional drones, mainly due to reduced energy and maintenance expenses [213]. 6.2. Policy Recommendations The current regulatory landscape for agricultural drones in India is overseen by the Directorate General of Civil Aviation (DGCA). As outlined in the rules and regulations regarding drones in Section 2, there were previously many challenges for farmers, such as mandatory remote pilot licenses, strict operational restrictions, and complex approval processes, which often led to high compliance

costs and limited adoption. Many farmers, especially small-scale operators, face bureaucratic hurdles and a lack of awareness about drone regulations. To address these issues, the Indian government took steps to reform drone policies and regulations in 2021. It introduced a fast-track approval system specifically for agricultural drones and eased licensing requirements for small-scale farmers [214,215]. There is a need to increase the number of licensing centers in rural areas and develop specific guidelines for agricultural drones. Furthermore, to encourage the use of drone technology in Indian agriculture, the government has launched various financial aid programs to assist institutions, farmer organizations, and individual farmers. These programs aim to lessen the financial burden of purchasing drones. 6.2.1. Institutional Financial Assistance Institutions under the Indian Council of Agricultural Research (ICAR), Farm Machinery Training & Testing Institutes (FMTTIs), Krishi Vigyan Kendras (KVKs), State Agricultural Universities (SAUs), and other public sector agricultural organizations are eligible for 100% financial assistance to purchase drones, up to a maximum of INR 10 lakhs per drone. This support enables demonstrations of agricultural drone applications in farmers' fields, promoting awareness and adoption at the grassroots level. Additionally, farmer producer organizations (FPOs) can receive grants covering up to 75% of the drone cost to conduct on-field demonstrations. For institutions that choose to rent drones instead of purchasing them, a contingency expenditure of INR 6000 per hectare is allocated to cover operational costs when leasing from custom hiring centers (CHCs), hi-tech hubs, drone manufacturers, or startups. In

contrast, institutions that own drones for demonstrations receive INR 3000 per hectare for operational expenses. 6.2.2. Financial Support for Custom Hiring Centers (CHCs) and Entrepreneurs To increase access to drone services for farmers, financial support is provided for establishing custom hiring centers (CHCs) under Cooperative Societies of Farmers, FPOs, and Rural Entrepreneurs. These CHCs receive 40% financial aid (up to INR 4 lakhs per drone) to offer affordable drone rental services to small and marginal farmers. Additionally, agricultural graduates establishing CHCs are eligible for 50% financial support (up to INR 5 lakhs per drone) to promote entrepreneurship in precision agriculture. 6.2.3. Individual Farmer Subsidies Small and marginal farmers, including those from Scheduled Castes (SCs) and Scheduled Tribes (STs), women farmers, and residents of northeastern states, are eligible for 50% financial assistance (up to INR 5 lakhs per drone). Other farmers can receive 40% support, with a maximum of INR 4 lakhs per drone for individual ownership. 6.2.4. Government Investment and Subsidy Disbursement As part of the Kisan Drone Promotion Initiative, the government allocated INR 129.19 crores to promote drone use in agriculture. This includes INR 52.50 crores assigned to ICAR for buying 300 Kisan Drones and holding demonstrations over 75,000 hectares through 100 KVKs, 75 ICAR institutions, and 25 SAUs. Additionally, financial support has been provided to various state governments for delivering over 240 Kisan Drones to farmers with subsidies and for setting up more than 1500 Kisan Drone CHCs to offer drone services at affordable prices [216]. 6.3. Training and Awareness Program The government has recognized the importance of providing skills and training in drone operation to help farmers adopt drone technology effectively. Initiatives like the program launched by Drone Destination and Indian Farmers Fertilizer Cooperative Limited (IFFCO), which offers drone pilot training exclusively for women as part of the "Lakhpati Didi Yojana," demonstrate efforts to close the skills gap in drone operation [24]. The scheme supports modernizing Indian agriculture by lowering labor costs. Additionally, this shows that perceptions of working women among rural Indians are changing. According to a government poll conducted in 2023, 80% of rural Indian men and a little over 41% of rural Indian women are employed in the formal sector [25]. By equipping women with the skills and knowledge to operate drones in agriculture, these training programs not only empower women but also improve farmers' overall ability to utilize drone technology for various farming activities. Additionally, these initiatives help develop a skilled workforce that can maximize the potential of drones in agriculture. Furthermore, to make drones more accessible at lower costs and empower rural women, several self-help group (SHG) initiatives have been established, including the "Namo Drone Didi" scheme, which was launched in December 2023. The scheme aims to train and equip 15,000 women SHGs for the 2024 to 2025 period, enabling women to work as drone pilots in the field. This initiative not only encourages technological adoption in rural areas but also lowers operational and drone purchase costs because fully trained women drone pilots receive a 30 kg drone free from the government [217]. Along with new drone regulations in 2021, India's Ministry of Civil Aviation launched a digital sky platform. The main goal was to train drone pilots for India's growing industry. As of September 2024, over 10,000 type-certified

commercial drones have been registered on this online system, simplifying drone registration, pilot certification, and licensing

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for commercial use. The platform is key in helping youth become trained drone pilots by offering a centralized certification system, connecting aspiring pilots with approved training organizations, and providing accessible information on airspace rules. Currently, there are more than 10,000 registered trained drone pilots in India. However, this number is expected to increase significantly, with officials projecting a need for 100,000 drone pilots in the coming years. The platform's impact goes beyond registration and training, supporting the broader drone ecosystem in India, including government efforts to boost drone use in agriculture through subsidies. To effectively address the skill barrier, the training curriculum typically combines theoretical knowledge, simulation exercises, and hands-on practical training. It includes regulatory compliance (such as DGCA regulations, drone registration, and pilot licensing), technical skills (drone components, flight planning, and simulator and actual flight training), agricultural applications (precision spraying, crop mapping, multispectral imaging, and data analysis), as well as safety protocols and record-keeping. Course durations range from short-term certifications of about 5 days to advanced programs lasting several weeks or months, sometimes incorporating mentorship and job placement support. Training costs vary among providers and programs: Private DGCA-certified courses typically range from INR 60,000 to INR 100,000 per participant, while many governmentsupported and Skill India initiatives offer free or heavily subsidized training, especially for farmers, SHGs, and farmer producer organizations (FPOs). Access remains a challenge since certified training centers are mostly located in urban and agricultural hubs, although some states have set up mobile and district-level centers to reach rural areas, as shown in Table 13. Many courses are now available in regional languages and in blended online– offline formats to enhance inclusivity and accessibility. Despite remaining challenges in cost and geographic coverage, these programs play a crucial role in developing a skilled drone pilot workforce in India, thereby encouraging wider adoption of drone technology in agriculture and supporting the government's vision for digital and precision farming [218]. Table 13. Drone training providers in India. Organization/Academy

Location

Notable Features/Curriculum

Typical Cost

Ref.

Drone verse

Pan-India

DGCA-certified, comprehensive agricultural curriculum

INR 60,000 (+GST)

[219]

Drone Academy of India

Multiple/online

100% placement, practical GIS/photogrammetry modules

N/A

[220]

Telangana Drone Academy

Hyderabad + rural

State-supported, hands-on and simulator training

Subsidized

[221]

Multiplex Drone

Pan-India

Simulator, hands-on, regulatory modules, log book

Moderate

[222]

Skill Digital India

Online

Free/low-cost “Kisan Drone Operator” course

Free

[223]

Garuda Aerospace, Drone Acharya, Eagletronics

Multiple

DGCA-approved, field mapping curriculum

N/A

[224,225]

6.4. Public–Private Partnership With government support, possibly through public–private partnerships, a sustainable model should be established. Subsidies are available to promote drone technology adoption, with significant financial aid provided to various groups. Currently, several government

policies and schemes support public–private partnerships (PPPs) in the development of agricultural drones. The Drone Promotion and Use Policy-2025, approved by the Madhya Pradesh government, aims to increase drone usage in agriculture and establish the state as a hub for drone technology. The Sub-Mission on Agricultural Mechanization (SMAM) provides grants for purchasing agricultural drones, covering up to 100% of the cost for various institutions and offering reduced percentages for farmer organizations and custom hiring centers. Additionally, the NaMo Drone Didi Scheme was launched for 2024–2026 with a budget of INR 1261 crores, aiming to provide drones to 15,000 selected women self-help groups for agricultural rental services and offering 80% financial assistance. Furthermore, the Production-Linked Incentive (PLI) scheme, initially introduced in September 2021, promotes drone manufacturing, component production, and software development. These policies and schemes have established a supportive environment for PPPs in agricultural drones. These drones-as-a-service (DaaS) models can enhance accessibility and lessen the financial burden on Indian farmers. They also include training, maintenance, and platform services. According to market forecasts, the DaaS sector is expected to grow from USD 130 million in 2020 to nearly USD 4.9 billion by 2030, with a compound annual growth rate (CAGR) of 44.4% (see Figure 7).

Figure 7. Projected growth of India’s drones-as-a-service (DaaS) market by segment (platform services, training, and MRO services) [226].

The above trend shows the growing feasibility of using service-based drones for smallholders, especially when paired with government initiatives like drone training and subsidies. It also highlights the expanding ecosystem around drone deployment, opening the door for broader agricultural transformation through service-oriented models. In addition, several research institutions in India play a vital role in advancing drone technology through public–private partnerships (PPPs). For instance, the Institute of Infrastructure, Technology, Research, and Management (IITRAM) in Ahmedabad has established a Centre of Excellence for Drone Technology to promote cutting-edge research and education in unmanned aerial vehicles (UAVs) [227]. Likewise, the Vishnu Institute of Technology launched a drone center of excellence in 2018–2019 and has formed collaborations with private companies, such as New Propeller Technologies R&D Pvt. Ltd. and Airosspace R&D Pvt. Ltd. [228]. Universities also provide specialized education through undergraduate and postgraduate courses, as well as Ph.D. programs and certification courses in specific drone applications. They

support industry collaboration by creating platforms for knowledge-sharing and building partnerships with private companies.

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6.5. Research Solutions In Table 14, some research-based solutions are listed that other authors have proposed to address these problems. These are the main concerns in drone implementation. Table 14. Solutions from different research scholars. Ref

Title

Keywords

[164]

Drone Charging Stations Deployment in Rural Areas for Better Wireless Coverage: Challenges and Solutions

5G, 6G Rural internet connectivity, Renewable energy, Network coverage,

[229]

Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges

Problem

Method

Solution

Limited onboard battery and scarce electricity supply in rural areas

Used simulation, three practical scenarios

Proposes using renewable energy stations to enhance UAV network performance, supported by simulation results

Smart farming, Bluetooth, Agricultural sensors, Cost

High costs and complexity in controlling UAVs could be barriers to adoption by farmers

Explores types of sensors suitable for smart farming.

Integration of Bluetooth smart-enabled sensors for farming applications

[230]

Survey of Drones for Agriculture Automation from Planting to Harvest

Robotic Process Automation, Image processing, Pattern recognition

Identifying the best applications of RPA and RS for maximum effect in agriculture

Analyzes the combination of RS technologies with UAS platforms for agricultural operations

Supports and develops a map or sensor-based variable rate application (VRA) using combined RS and UAS technologies

[231]

Technology Acceptance among Farmers: Examples of Agricultural Unmanned Aerial Vehicles

Farmer’s decision, Agricultural innovation

Limited information on the adoption of agricultural drones by farmers

Face-to-face surveys with 384 farmers

Government support Interest-free loans Renting over purchasing Cooperative help

[232]

Intelligent Cyber-Security System for IoT-Aided Drones Using Voting Classifier

Small drones, Cybersecurity, Privacy

Current small drone designs do not meet data transformation and privacy requirements for secure operation in civil and defense industries

Analyzes recent privacy and security trends Proposes a framework to enhance data transformation and privacy mechanisms in small drones

Employs intelligent machine learning models to enhance the security and adaptability of IoT-aided drones

Qin et al. highlight the difficulties of providing internet access in rural areas and examine the potential of UAV-assisted networks powered by renewable energy charging stations. The proposed solution, backed by simulation results, indicates that this integration could be a practical way to address the limitations of UAV onboard battery life in rural regions. Future work and challenges in this field are also discussed [164]. Maddikunta et al. explore the potential of UAVs in smart farming, focusing on the importance of affordable and easy-to-operate control technologies. They propose using smart Bluetooth for UAV control and discuss the types of sensors used and the challenges faced. The study also highlights future roles for UAVs in agriculture, aiming to motivate farmers by addressing cost and control issues [229]. Kulbacki et al. examined how robotic process automation, image processing, pattern recognition, and machine learning can be combined with drones and satellites to improve precision agriculture. It emphasizes the advantages of high-quality remote sensing and the possibilities for variable-rate application, even though there is no unified legislation on drone use [230]. Parmaksiz and Cinar explore factors influencing farmers' adoption of agricultural drones through face-to-face surveys and various analytical methods. The results emphasize the importance of government support, a preference for interest-free loans, and a greater willingness to rent rather than buy UAVs. These findings help identify farmers who are more likely to adopt UAV technology and offer valuable insights for decision-makers and market players to encourage its use in agriculture [231]. Majeed et al. examined the privacy and security issues with the Internet of Drones (IoD), emphasizing the vulnerabilities of small drone networks. They propose a new framework that uses intelligent machine learning models to improve data handling and privacy measures. This framework aims to protect drone networks from interception and intrusion, and its effectiveness has been confirmed with a benchmark dataset, showing strong results [232].

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6.6. Case Studies 1.

Cost Reduction and Entrepreneurial Impact of Drone Adoption in Rajasthan

This case study relies on publicly available reports from Indian news outlets and interviews with local stakeholders. It highlights the economic potential and scalability of drone use among tech-savvy young farmers. In Hanumangarh district, Rajasthan, Ashish Beniwal, a 24-year-old engineering graduate, successfully adopted drone technology for agricultural purposes. After completing pilot training and obtaining the necessary license, he bought a 10 L agricultural spraying drone for INR 9.5 lakh in 2023. He applied drone technology to crops like paddy, cotton, guar (cluster bean), and sugarcane, achieving the following significant reductions in input costs.

• •

Pesticide and fertilizer costs for 30 bighas (approx. 7.5 acres) decreased from INR 2 lakh to INR 25,000, as shown in Figure 8; He reported a 40–50% decrease in chemical usage while maintaining crop yields.

Figure 8. Input cost comparison before and after drone adoption in the Rajasthan case study.

Ashish also provided commercial drone services, covering 5000 bighas across Hanumangarh, Sriganganagar, and parts of Haryana, charging INR 200–250 per acre. His entrepreneurial effort not only created an additional revenue source but also encouraged fellow farmers, like Kuldeep Jalap, to start using drone services for their fields. While Ashish's experience highlights the economic viability and scalability of drone technology in Indian agriculture, such cases are currently limited to individuals with access to capital, technical skills, and formal training. However, with increasing government support, training programs, and targeted subsidies, the potential to replicate similar models across rural areas is expanding. Broader adoption will depend on expanding institutional support, improving affordability, and raising awareness among smallholder farmers [233]. 2.

Case Study: Adoption of Agricultural Drone Technology by a Woman Farmer in Punjab, India

This case is based on official coverage of the Drone Didi initiative, a government program launched in 2023 to train 15,000 rural women in drone operation. Jaswinder Kaur Dhaliwal's story illustrates its transformative potential. Jaswinder Kaur Dhaliwal, a 46-year-old woman from Rattian village in Moga, Punjab, was selected for training under the Drone Didi initiative, a government project aimed at training 15,000 women in agricultural drone applications [234]. Initially unfamiliar with drone equipment, she overcame her hesitation after receiving structured training in Gurgaon through the Indian Farmers Fertilizer Cooperative Limited (IFFCO) [235].

After completing her training, she started providing commercial drone-spraying services in June 2024. Her reported results include the following.

• • • •

Spraying over 200 acres of farmland at INR 250 per acre (see Figure 9b); Demonstrating efficiency improvements over manual spraying (usually INR 200 per acre); Reducing spraying time to 7 min per acre (see Figure 9a); Receiving positive farmer feedback on pesticide and fertilizer coverage.

(a)

(b)

Figure 9. (a) Spraying time per acre: manual vs. drone method; (b) cost per acre for spraying: manual vs. drone method.

To promote drone adoption, Jaswinder visited nearby farms and offered free one-acre demonstrations. In one case, this led to requests for drone spraying over 58 acres [236]. Beyond agriculture, she sees drone work as a way to address local social issues, especially among women. She said: "Drones are being used to supply drugs in Punjab, but I think only women can stop the drug menace by engaging themselves in such positive work" [237]. This case is not an isolated incident but reflects a growing national effort to include women in modern agriculture through drone technology. As part of the Drone Didi initiative, Jaswinder's story demonstrates how organized training, affordable access, and targeted government programs can empower rural women and create entrepreneurial opportunities. While adoption is increasing, especially among self-help groups (SHGs) and farmer producer organizations (FPOs), broader success will depend on ongoing investment in infrastructure, affordability, and outreach that includes underserved regions.

- Conclusions, Future Directions, and Open Issues This study provided a thorough review of drone adoption in Indian agriculture, examining its advantages, challenges, and future prospects. It started by identifying the ongoing issues faced by Indian farmers, such as fragmented landholdings, low productivity, and limited access to modern technologies. In response, the paper assessed how drone technology—enhanced by AI, IoT, and precision tools—can revolutionize agricultural practices by increasing efficiency, lowering input costs, and promoting sustainability. This review examined the Indian drone market's expected growth in the coming year. Several domestic and international companies are emerging as major players in this field, contributing to hardware development, service delivery, and AI-driven analytics customized for agriculture. This review also examined the regional mindset differences between small-scale and large-scale farmers regarding drone adoption. Although there is increasing interest and positive social perception toward drone use, challenges still exist, especially high initial

costs, limited technical training, and insufficient infrastructure. These issues were analyzed from technological, economic, and social perspectives. To overcome these barriers, the paper highlighted several solutions. These include policy recommendations such as institutional financial assistance, custom hiring centers, and individual subsidies. Additionally, public–private partnerships and service-based models like "drone-as-a-service" provide scalable, low-cost options for smallholder farmers. Training and awareness programs are also essential for building farmer capacity and encouraging long-term technology adoption. Finally, this study

highlights future directions and open challenges, stressing the importance of affordable models and better accessibility to promote the widespread use of drones in agriculture. Limitations: This study was limited by its reliance on secondary data, which may not fully reflect real-time field challenges. However, this approach allows for a broad analysis of current trends, policies, and potential solutions, serving as a foundation for future empirical research. Although the study discusses policy recommendations, it may not fully address the practical challenges of implementing these policies at the ground level. Additionally, a more thorough examination of the potential long-term environmental impacts of widespread drone use in agriculture could improve the overall comprehensiveness of this study. Future directions: Future research can explore autonomous drone technology for agriculture. Currently, a human operator is needed for drone operations. However, efforts are underway to enable drones to operate autonomously without human intervention, primarily using AI. The integration of AI and machine learning has greatly improved drone capabilities, allowing them to detect pests, assess crop health, and make data-driven decisions in real time [238]. An innovative advancement is the incorporation of generative AI technology, which provides sophisticated onboard processing for adaptive mission planning and better object recognition without depending on ground-based systems. Additionally, swarm technology has gained popularity, enabling multiple drones to collaborate efficiently, expand coverage for large-scale operations, and support coordinated actions for complex agricultural tasks. Autonomous drones are becoming essential to precision agriculture, providing high-resolution imaging, real-time crop monitoring, and targeted resource application. They are equipped with advanced sensors, including multispectral and hyperspectral sensors for detailed plant health analysis and LiDAR technology for accurate 3D mapping [239]. Moreover, incorporating blockchain technology into drones is a key area of research. The combination of blockchain with drones is a quickly growing application, but it is not yet a mainstream or widely adopted industry practice. While promising pilot projects and research show their potential, most real-world deployments remain in the early stages [240]. Blockchain offers a strong security measure for drone operations. For example, drones generate and transmit sensitive data such as video, sensor readings, and location information, often over insecure wireless networks. Blockchain can provide a decentralized, tamper-proof ledger for storing these data, ensuring they cannot be altered or accessed without authorization. This is especially important for drones used in security, surveillance, and emergency response, where data integrity is crucial [241]. Additionally, Blockchain can assign unique cryptographic identities to individual drones, allowing only authorized users or systems to control them and access their data. This minimizes the risks of hijacking and unauthorized interference in drone missions, such as package delivery and surveillance flights [242]. While companies and researchers are actively exploring and testing these applications, blockchain-enabled drones are not yet common in commercial or government fleets. How-

ever, as drone use grows and the need for secure, autonomous, and scalable management increases, blockchain is expected to play a bigger role in supporting trusted, decentralized drone operations in logistics, defense, emergency response, and other sectors [243]. Open issues: To complete our overview, we outline some unresolved questions and research challenges that need to be addressed for the smooth operation of drones.
(1)

(2)

(3)

(4)

(5)

(6)

Privacy concerns: Privacy is the biggest issue for drone flights. Cybersecurity for drone systems is crucial to prevent hacking, hijacking, and other cyber threats. There is a need to develop strong encryption protocols, secure communication channels, and tamper-proof hardware [244,245]. Researchers are working on advanced authentication methods to ensure that only authorized users can operate drones [246]. Additionally, research has focused on creating secure software update systems and using blockchain technology for safe data transmission and storage [247]. Regulatory framework: Creating comprehensive and flexible regulations is

crucial for overseeing drone operations across various sectors of agriculture. This includes establishing clear guidelines for drone registration, pilot certification, and operational limits. Ongoing efforts involve developing standards for drone identification and tracking systems to improve accountability and support effective law enforcement. Payload optimization: Enhancing payload capacity and efficiency while maintaining flight performance and safety is vital for broadening drone applications. This involves researching lightweight, high-strength materials and advanced structural designs to improve payload-to-weight ratios. Engineers are developing modular payload systems that enable quick and easy reconfiguration of drones for various missions [248]. Human drone interaction: Creating intuitive interfaces and control systems for both professional operators and casual users is vital for widespread drone adoption. This includes designing user-friendly ground control stations with clear graphical interfaces and simplified flight controls. Ongoing efforts involve developing autonomous systems that can interpret high-level commands from users and convert them into complex flight maneuvers [249]. Environmental impact: Evaluating the ecological effects of widespread drone use is essential for sustainable operation. This requires thorough studies on how drones affect wildlife, especially birds and flying insects. Researchers are creating quieter, more eco-friendly propulsion systems to reduce ecosystem disturbances [250]. Further research is necessary to examine the potential positive environmental uses of drones, such as wildlife conservation, pollution monitoring, and reforestation efforts [251]. Open questions: Some additional remaining questions are as follows.

• • • • •

How to ensure smooth integration of drone technology with existing farm management practices and equipment; How to handle concerns about data collection, storage, and sharing in dronebased agriculture; Assessment of the long-term ecological impacts of widespread drone use in agriculture; Establishing consistent international standards for agricultural drone operations; Improvement in battery life and alternative power sources for extended drone operations.

These research areas and open issues offer opportunities for further progress in the field of agricultural drones, which could result in more efficient, sustainable, and productive farming practices in India and around the world.

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Chapter 1

Drones Here, There and Everywhere Introduction and Overview Bart Custers

Abstract This chapter provides an introduction to this book and an overview of all chapters. Given the popularity of drones and the fact that many of them are easy and cheap to buy, it is generally expected that the ubiquity of drones will significantly increase within the next few years. This raises questions as to what is technologically feasible (now and in the future), what is acceptable from an ethical point of view and what is allowed from a legal point of view. Drone technology is to some extent already available to consumers and more drone technologies are expected to become available to consumers in the near future. The aim and scope of this book: to map the opportunities and threats associated with the use of drones and to discuss the ethical and legal issues of the use of drones. Since drones have many names, including UAVs, UASs and RPASs, the terminology used is explained. This chapter concludes with an overview of the structure of this book, containing chapters on drone technology, the opportunities and threats of drone use, ethical and legal issues concerning the use of drones and potentials solutions for these issues. Keywords Drones · UAV · UAS · RPAS

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1.1 The Rise of Drones Mrs. Lisa Pleiss lives in Seattle on the 26th floor of an apartment building. In June 2014 she looked out of her window and saw a drone that seemed to react to her gaze. It appeared to her that there were video cameras on the drone. Mrs. Pleiss was surprised and immediately distressed. Since Mrs. Pleiss lives on the 26th floor, she previously never had to worry about someone peering into her apartment. When she alerted the building management to the presence of the drone, they observed two men outside the building who seemed to be the ones operating the drone. The men quickly disappeared when they saw the management observing them. In the city of Seattle, drones are currently legal to fly, but are not permitted to photograph the inside of someone's home.1 In October 2014, two Dutch filmmakers in the Dutch city of Utrecht used a drone to take stunning pictures of the Dom tower, which was surrounded by mist.2 The Dom is the tallest church spire in the Netherlands, built between 1321 and 1382. The owner of the drone used by the filmmakers received a fine of 350 Euro for using it to photograph the tower. According to Dutch laws, it is illegal to fly a drone without special permission. Furthermore, private drone owners are only allowed to fly drones during the day while the drone is operated in visual line of sight at all times. Additionally, drones may not fly above buildings and people. In early 2015, people started to report drone sightings over Paris.3 More than a dozen drone sightings over sensitive areas of the French capital were reported to the police. The flights reportedly took place overnight near the river Seine, Place de la Concorde, the Invalides military museum and around the Paris ring-road. Perhaps more worrying, drone sightings were reported over French nuclear plants 1 Bradwell 2014. 2 http://www.dutchnews.nl/features/2014/11/the-dom-tower-in-utrecht-by-drone/. Accessed April

1, 2016. 3 http://www.theguardian.com/world/2015/mar/04/drone-sightings-paris-seine-concordeinvalides. Accessed April 1, 2016.

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since October of 2014. For some time, it was unclear whether the drone flights were the work of pranksters, tourists or terrorists. However, in early 2015, the police arrested Al Jazeera journalist Tristan Redman, who was fined 1000 euro.4 The examples above illustrate the rise of drones in the public space. Civil drones are a relatively new phenomenon in our society. Previously drones were mostly employed in the military domain, for warfare in remote zones in places such as Afghanistan. The use of drones in the military domain got the discussion on drone use started and constituted the basis of the civil market for drones. As a result, these days small drones for civil (non-military) use are increasingly available for purchase by civilian consumers, because they are increasingly inexpensive and easy to buy. For less than a hundred euros, small drones can be purchased in toy stores or via the Internet. For a couple of hundred euros more, one can buy professional drones with advanced photo and video cameras. Most of these small non-military drones for sale to consumers weigh up to several kilograms and can fly within a range of a couple of meters to a several hundred meters. The possibilities for the use of drones can be found in virtually all sectors of society. In the public sector drones can be used in the prevention of crime, in making reconstructions of crime scenes, in countering disasters, for dike inspections, geological surveys,5 countering fraud, guarding borders,6 and for environmental and agricultural inspections.7 In the private sector there is potential for camera applications, to make aerial photographs, to help prevent neighbourhood crime and to support population census estimations. Drones also offer greater possibilities in the field of cinematography, television and other entertainment.8 Additionally, there are numerous potential applications for drones equipped with various payloads, such as drones with heat sensors to detect cannabis plantations, drones that carry water, food or medicine for rescue operations, and drones with pesticides for use in agriculture. In the military domain, drones are used for several purposes, including deployment in conflicts. The potential of drones is offset by the threats that make drones the target of damage, the means of inflicting damage, or an environmental factor responsible for damaging effects. Some

people may deliberately try to damage or steal drones or their payloads, including collected data. Others may use drones as a means of inflicting damage, such as (intentional) security or privacy threats, using drones to collide with people or objects,9 to drop certain (hazardous) payloads,10 and to spy on other people or annoyingly monitor them. Non-intentional environmental

4 BBC News 2015. 5 Parker 2014; Dillow 2013. 6 Caroll 2014; Stewart 2014; Preston 2014. 7 Wozniacka 2013. 8 CBS News 2014. 9 Heine 2013. 10 Chosun 2014.

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safety risks include various threats regarding air traffic (crashing, colliding, etc.).11 Drones may violate privacy in different ways, e.g., by harassing people (or, at the least, causing nuisance and annoyance), by their large-scale (legal or illegal) collection of personal data, inadequate transparency regarding what data are collected and how that data are used. Drones are also subject to 'function creep' (using data for purposes other than those for which they were originally collected).12 In the military domain, drone use may cause civilian casualties. Given their popularity and low cost, drones will become significantly more ubiquitous in the next few years. This raises questions as to what is technologically feasible (now and in the future), what is acceptable from an ethical point of view and what is allowed from a legal point of view. Drone technology continues to evolve. In support of further research and debate, this book aims to map the opportunities and threats associated with the use of drones and to discuss their ethical and legal implications. This chapter provides an introduction to this book and an overview of the chapters that will follow. This first section briefly introduces the premise of this book, including its scope and intended audience, and what inspired us to write it. Section 1.2 provides a brief history of drones. Next, Sect. 1.3 describes the terminology used in this book (since drones are referred to in many ways, including terms such as UAVs, UASs and RPASs).13 Finally, Sect. 1.4 sketches the structure of this book and introduces all chapters that follow.

1.1.1 What This Book Is About This book aims to map the opportunities and threats associated with the current and future use of drones and to discuss the ethical and legal issues of drone use. As such, this book is useful as a reference for further research and debate, such as directions for desirable or undesirable technological developments, necessary, useful or unwanted applications of drones and possible regulation of drone technology and drone use. The scope of this book includes existing drone technology and drone practices as well as technologies and applications under development or expected to materialize within the next 5–10 years. In Chap. 2, technological developments such as further miniaturization, increased flight autonomy and the use of swarms of drones are discussed. Although this book provides information about drone technology in order to understand possibilities and threats and the ethical and legal issues raised by

11 CASA 2013. 12 See also Finn et al. 2014. 13 UAV:

Unmanned Aerial Vehicle, UAS: Unmanned Aircraft (or Aerial) System, RPAS: Remotely Piloted Aircraft System.

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drones, it does not primarily have a technological focus. Rather, it deals with the social, ethical and legal effects of drone technology. The societal effects are discussed in terms of opportunities and threats. Ethical issues are discussed in terms of which types of drone use may violate important moral values and principles, which moral conflicts may occur and which types of drone use may call for applying moral principles in new ways. Legal issues are discussed in terms of analyses of current legal frameworks (what is allowed?) and envisioned legal frameworks (what should be allowed?). Ethical, legal and societal issues relate to, inter alia, privacy, trust, liberty, dignity, equality and possible chilling effects resulting from drone use. Countries have different viewpoints on and different legal regimes for drone use. The authors contributing to this book present perspectives from different countries. However, since drone technology is an international development (drones are often and easily sold across borders), many of the opportunities, threats and ethical and legal

issues discussed are universal. For example, many legal issues are the same across different jurisdictions. For example, aviation laws have a strong international orientation and many countries apply similarly strict regulations that aim to prevent a too liberal use of drones, mainly for reasons of air traffic safety. Simultaneously, many countries are studying whether the regulations are sufficient to cope with current and future developments, and are debating which types of drones use should be permitted. There are no real frontrunners here. Most Western countries are still debating drone use and possible amendments to rules and regulations. Due to the speed of many technological developments, it is sometimes difficult for people without a technological background to understand how these technologies work and what impact they may have. This book attempts to explain the latest technological developments with regard to drones in a straightforward manner. Similarly, experts in drone technology may not always be aware of the legal and ethical perspectives. As such, this book can be of value to academics in several disciplines, such as law, technology, ethics, sociology, politics, and public administration. Furthermore, this book may be of value to people who may be confronted with the use of drones in their work, such as those working in the military, law enforcement, disaster management and infrastructure management. Individuals and businesses with a specific interest in drones are also part of the target audience for this book.

1.1.2 The WODC Research Project The idea for this volume on drones came from research that we carried out at the WODC, the research centre of the Ministry of Security and Justice in the Netherlands.14 Both the Dutch parliament and the Dutch government requested 14 http://www.wodc.nl. Accessed April 1, 2016.

this research in order to obtain more knowledge and information on the use of drones. This research was carried out in 2014 and published (in Dutch) in 2015.15 The research approach was based on an extensive literature study, including scientific literature, professional literature and media messages with regard to the use of drones, and interviews, held with experts in various disciplines, including scientists who develop drones, companies that manufacture or use drones, companies that offer drone services and organizations that purchase such services, organizations in the security sector and scholars in the fields of privacy, ethics and human rights. In total, interviews were held with 17 individuals with the aid of a semistructured questionnaire, complemented by conversations with about the same number of people of other organizations. The research report was submitted to the Dutch Minister of Security and Justice, who sent the research report to the Dutch Parliament indicating that he would come up with more detailed plans for the use of drones in the course of 2015. Some plans were presented and discussed in the Dutch Parliament on 21 September 2015, but during this debate it became clear that more detailed plans are needed in the coming years. Apart from the research report mentioned above, researchers, policymakers and other experts in the field of drones and drone use were invited via a call for papers to submit chapters for this book. This was done via both a targeted approach, addressing authors of drone literature, and via posting and distributing the call for papers via websites and email. As a result, almost 30 abstracts were received, from which the authors of approximately 20 abstracts were invited to submit a full chapter. These chapters went through a double blind review process, after which some chapters were rejected or withdrawn. The call for papers opened in early 2015 and the final manuscript was ready end of 2015.

1.2 A Brief History of Drones The recent media attention for drones suggests that civil drones are a new phenomenon and that such drones are a new technology. However, drones have existed for almost a century.16 What is new, though, is the fact that today drones are small, relatively inexpensive and easily available. Drones sales figures are hard to find, but millions of drones have already been sold.17 Amazon is selling more than 10,000 drones a month. In order to better understand where drone technology is heading, this section provides a brief history of drones.18

15 Custers et al. 2015. 16 HSD 2014. Depending on definition, drones exist even longer. There are examples of aircraft without persons on-board during the American Civil War. 17 Reagan 2015. 18 For a detailed account of the historical development of drones, see also Villasensor 2013.

The earliest unmanned aircraft were probably (hot air) balloons. However, these balloons are generally not considered drones, mainly because their flight cannot be controlled.19 During World War I, radio control techniques were used to build unmanned aircraft. The first flight of the Hewitt-Sperry Automatic Airplane was in 1917.20 This airplane was developed as an aerial torpedo, for military purposes, and is considered to be a flying bomb and precursor of the cruise missile.21 In 1918 was the first flight of the Kettering Bug, an unmanned aerial torpedo capable of striking ground targets in a range of 120 km, while flying at 80 km/h.22 World War I ended before the Kettering Bug could be deployed. After World War I, airplanes were converted into drones. Examples are the Larynx (1927), the Fairy Queen (1931) and the DH.82B Queen Bee. The name Queen Bee is said to have led to the use of the term 'drone' (a male bee) for pilotless aircraft.23 During World War II, the Radioplane Company manufactured nearly 15,000 drones of the Radioplane OQ-2 for the US Army. 24 As such, it was the first massproduced drone. This drone was launched with a catapult and recovered by parachute. The later version, the OQ-3 was also widely used during World War II, with over 9400 being built during the war. After World War II, drones were also used for purposes other than being or dropping bombs. The first drone for aerial reconnaissance was the MQM-57 Falconer.25 This drone had its first flight in 1955. It was a 124 kg aircraft that could carry cameras and illumination flares for night reconnaissance.26 Over 73,000 were built and used in at least 18 countries. During the Vietnam War, the US used Ryan Firebee drones,27 which were developed in 1951. These drones were launched from Hercules transport aircraft, which could carry four Firebee drones in total, two attached under each wing. More than 7000 Firebees were built and, although production ended in 1982, some of them are still in service. For example, five (modernized) Firebees were used to lay chaff corridors (radar distraction with thin pieces of aluminum, metalized glass fibre or plastic) during the 2003 invasion of Iraq.

19 Note that from a legal perspective, balloons may be considered (unmanned) aircraft, see also

Chap. 13. 20 https://en.wikipedia.org/wiki/Hewitt-Sperry_Automatic_Airplane. Accessed 1 April 2016. 21 Werrell and Stevens 1985. 22 Zaloga 2008. See also https://en.wikipedia.org/wiki/Kettering_Bug. Accessed 1 April 2016. 23 Yenne 2004. See also https://en.wikipedia.org/wiki/History_of_unmanned_aerial_vehicles. Accessed April 1, 2016. 24 https://en.wikipedia.org/wiki/Radioplane_OQ-2. Accessed April 1, 2016. 25 Anonymous 1956. 26 https://en.wikipedia.org/wiki/Radioplane_BTT#MQM-57_Falconer. Accessed April 1, 2016. 27 https://en.wikipedia.org/wiki/Ryan_Firebee. Accessed April 1, 2016.

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Since 1995, the US Air Force and the CIA have used the MQ-1 Predator drone for military reconnaissance and combat.28 It has been used in Afghanistan, Pakistan, Bosnia, Serbia, Iraq, Yemen, Libya, Syria and Somalia.29 The Predator carries cameras and other sensors and can carry and fire missiles. Predators have also been used for border enforcement, scientific studies and forest fire monitoring. Predators are over eight meters long, with a wingspan of almost 15 m, weigh 512 kg (empty), can fly at a speed of 130–165 km/h, with a range of 1110 km and an endurance of 24 h. The Predators can be remotely flown from great distances, with operators in US-based control rooms while the Predators fly in overseas war zones. In 2013 the total number of Predators built was 360 and most of these are still in service. One Predator costs about 4 million US dollars. A larger, heavier and more powerful version of the Predator is the MQ-9 Reaper. The Reaper was first used in 2007 in Iraq and Afghanistan and is still in service. In 2010, 104 Reapers were built, each costing almost 17 million US dollars.30 The Reaper is 11 meters long, has a wingspan of 20 m, a weight of 2223 kg (empty), a cruising speed of 313 km/h, a range of 1852 km and an endurance of 14 h. Reapers have two on-board weapons systems and up to four missiles and two laser-guided bombs as payloads. It may be clear from this brief overview that drones were mainly developed in a military context and its use in this context is still very common, even on the increase. However, as mentioned in the previous section, drones now also offer many civil (non-military) applications. Both military and civil drone use are addressed in this book. A more detailed description of civil drones and their applications can be found in Chap. 2.

1.3 Terminology An important issue when talking about drones is which terminology to use. The term drone typically refers to an aircraft that does not carry a pilot on-board and is instead operated from a ground control system or is able to fly (to some extent) autonomously. In literature and in practice, there are many other terms that refer to drones. The different terms do not always have exactly the same scope and different stakeholders prefer using different terms. In this section, we will discuss the most common terms and how they are used and then explain why the term ‘drones’ has been chosen as the leading term in this book. Drones The term drone is the term that the media use and, therefore, the term that is best known among the general public. Drone is originally the English word for a male 28 Whittle 2014. 29 https://en.wikipedia.org/wiki/General_Atomics_MQ-1_Predator. Accessed April 1, 2016. 30 Note that these costs for the drone do not include costs for ground stations, satellite use, etc.

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bee. In other languages, such as French, German, Italian, Spanish, Russian and Dutch, the word drone is also commonly used, although it is sometimes written slightly different (Drohne in German, dron in Spanish, дрон in Russian). The term drone was originally used in military applications and for many people it still retains that connotation. Clarke (2014) traces the first use of the term drone to the US Navy in 1935.31 This military connotation is slowly shifting and drones are increasingly associated with civil drones used closer to home. Accordingly, the images associated with the word drone are slowly shifting from a military unmanned airplane flying above Afghanistan to a small helicopter, usually equipped with a camera, that is remotely controlled by a smartphone. The term drone includes unmanned airplanes and helicopters, but usually does not include unmanned balloons, unmanned flying platforms, rockets and unmanned jetpacks. The term drone is not used in any kind of legislation. UAV and UAS Apart from the term drone, the most often used terms are Unmanned Aerial Vehicle (UAV) and Unmanned Aerial System (UAS).32 The term UAV focuses on the flying platform (and its payload, if any), whereas the term UAS is a more general term to refer to both the flying platform and the ground station that controls the platform. These more descriptive terms are used in the US and other English speaking countries, but also in some other countries. In practice, the terms UAV and UAS refer to the same aircraft as the term drone (i.e., unmanned airplanes and helicopters, but not, for instance, rockets and jetpacks). The terms UAV and UAS are used mainly in official documents, including legislation.33 The general public is less familiar with these terms, especially when the abbreviations are used. As a result, people may have few or none associations with these terms. Professional drone users obviously are familiar with these terms and use them as equivalents for the term drone. Some people assume that the terms UAV and UAS have a weaker military connotation than the term drone, whereas others think the abbreviations UAV and UAS have a stronger military (euphemistic) connotation. RPAS Another often used term is that of Remotely Piloted Aircraft Systems (RPAS). The term RPAS is used to describe unmanned aerial systems that are remotely controlled by a pilot. As such, it differs from the terms drone, UAV and UAS, since the term RPAS assumes that there is a pilot, whereas this is, strictly speaking, not necessarily the case for drones and UAVs. As will be explained in Chap. 2, there are technological developments in which drones can fly increasingly

31 Clarke 2014. 32 Note that the term UAS is sometimes explained as the abbreviation of Unmanned Aircraft

System as well. 33 Note, however, that the term UAV is often used as an alternative to other terms and is not as frequently used as the term UAS. See also Chap. 13.

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autonomously, for instance, pre-programmed or self-learning. Hence, all RPASs are UAVs, but not all UAVs are RPASs. The term RPAS refers more to radio control airplanes and helicopters and excludes fully autonomously flying aircraft. As such, the term RPAS refers to a subset of drones or UAVs. The term RPAS is often used in policy documents in Europe. Outside Europe, this term is used less often. Other Terms There are also other terms that are used, but these usually refer to subsets of drones. Examples are Unmanned Combat Aerial

Vehicle (UCAV), Micro Aerial Vehicle (MAV) and microcopter. Radio control aircraft and model airplanes also indicate subsets of drones, usually drones for recreational purposes. In this book, these terms as well as the term RPAS will only be used when particular reference to these subsets of drones is made. As the title of this book indicates, this is a book on drones. As such, the term drones is the term used in this book. The terms UAV/UAS are used when referring to specific documents, contexts or quotes.

1.4 Structure of This Book 1.4.1 Part I: Introduction Part I of this book explains the basics of drones, drone technology and drone use. The sections above already dealt with the scope of this book, the history of drones and drone terminology. In Chap. 2, Vergouw, Nagel, Bondt and Custers elaborate on the basics of drone technology. They explain the different types of drones by their model (fixed-wing, multirotor, etc.), their degree of autonomy, their size and weight and their power source. These specifications determine the drone's cruising range, the maximum flight duration and the payload capacity. The payloads, in turn, largely determine the possible applications of drones. Payloads can be different types of sensors, like cameras, sniffers and meteorological sensors, or cargo, like mail, parcels, medicines and fire extinguishers. Since most drones use wireless communication with a pilot on the ground and also often have payloads that use wireless communication, frequency spectrum issues are discussed. Finally, Vergouw, Nagel, Bondt and Custers discuss future developments in drone technology, particularly the trends that drones become smaller lighter and more efficient and trends in (increased) autonomy and drones operating in swarms. In Chap. 3, Finn and Donovan examine the intersection between drone data and Big Data. Drones are increasingly becoming Big Data collection platforms, as they are (more and more by default) equipped with an increasing set of sensors. Apart from the visible appearance of drones in the sky, most drone use also involves a largely invisible process of collecting and processing data. Finn and Donovan focus on two uses of drones for civil purposes, crisis informatics and

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precision agriculture, which are not considered to raise significant ethical and privacy issues, as they do not focus on people. By closely scrutinizing these examples of drone use, they show that even those drone applications that may initially seem low risk from ethical and privacy perspectives raise issues on the identifiability of individuals, large-scale discrimination or inequalities in relation to particular social categories and the digital divide. As such, there is a need to move beyond the distinction of high risk versus low risk drone use. Instead, it is necessary to consider ethical and legal issues of drone use more in-depth for specific technologies, enabling specific applications in specific contexts.

1.4.2 Part II: Opportunities and Threats Before discussing ethical and legal issues of drone use it is useful to investigate specific applications of drones in specific contexts. Part II of this book therefore provides several chapters on drone use in different areas of society. Drone technology is a typical example of dual-use technology: it may be used for better or for worse. Hence, Part II of this book deals with both opportunities and threats of drone use. It should be noted that opportunities and threats may strongly depend on someone's perspective. For instance, one person may value the opportunity drones provide to make beautiful pictures of their neighbourhood whereas someone else in the same neighbourhood may consider the same drone as a violation of their privacy and a nuisance due to the noise the drone generates. In Chap. 4, Applin explores the feasibility of delivery drones in the context of American cities and neighborhoods. While the use of delivery drones may be cheaper and faster to rural areas, the idea of delivery drones in cities and suburbs requires careful consideration, for it has the potential to disrupt and change community culture. Applin discusses the current delivery climate, the rise in volume of package deliveries (in no small part due to Internet shopping) and the practical and cultural hurdles to overcome if delivery drones are to become viable. Applin examines aspects of drone delivery such as trust, privacy, security, and the roles that current delivery drivers play in the fabric of communities, including sociability. Sociability takes on a new role in drone delivery and in Chap. 4 Applin explores how ubiquitous drones will be required to become more 'social' with each other and with communities in order to cooperate, communicate positions and negotiate for space (to avoid overlap in routes) to avoid accidents. In Chap. 5, Engberts and Gillissen focus on drone use by the police. They describe how

police and law enforcement agencies can and already do benefit from drones. The police can perform many of their tasks, including maintaining public order, criminal law enforcement, assisting those in need and safeguarding VIPs or sensitive objects better and faster with the use of drones. Engberts and Gillissen distinguish between drones for sensing (when cameras, heat sensors

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and sniffers provide opportunities for observation, monitoring and detection) and drones as tools (when drones use light or sound or even weapons like pepper spray to prevent disturbances of the public order and other threats). Focusing on the police forces in The Netherlands, they examine both legal conditions (such as included in the Police Act, the Local Government Act and the Code of Criminal Procedures) and practical conditions (such as aviation procedures, safety rules, geographical and physical elements and weather conditions). In Chap. 6, Marin focuses on drone use for border surveillance. The deployment of drones in border surveillance, a competence shared between the EU and its member states, may have several functions, including the reduction of the number of illegal immigrants, the increase of security in the EU by preventing crossborder crime and the enhancement of search and rescue operations for illegal immigrants and boat refugees that try to reach the EU. By describing recent developments, such as EUROSUR and the Italian operation Mare Nostrum, the use of drones in border surveillance is illustrated. Marin concludes that the use of drones in border surveillance is not per se based on a mainly humanitarian rationale, but is rather aimed at increasing surveillance and intelligence. As such, drones in border surveillance mainly have a securitization function regarding borders as gateways for security threats. In Chap. 7, Martini, Lynch, Weaver and Van Vuuren examine the use of drones for humanitarian use. Drones can be very useful for temporarily restoring communication networks and for delivering critical relief items after a disaster. Drones have already been deployed by humanitarian actors in Haiti and the Philippines for mapping and improved situational awareness and needs assessments of the region. In the Democratic Republic of Congo, long-range drones have significantly improved data reconnaissance and data gathering. Closer to home drones are deployed during sport and other events, for instance, carrying camera technology and AEDs. Apart from these and other examples of drone use, Martini et al. describe how, by means of global dialogues, guidelines and recommendations for drones and other emerging technologies were developed to make urban communities more resilient. In Chap. 8, Michaelides-Mateou focuses on the use of drones by terrorists. Drones are obviously an innovative tool, providing lots of opportunities but also several threats. As such, drones may be an appealing weapon choice for terrorists to deliver mass destruction, as they may contribute to more victims, panic and visibility of terrorist attacks. For terrorists, drones have a number of advantages: drones can be used to easily deliver biological, chemical and even nuclear agents, drones can be operated without any special training, knowledge or skills, drones are easily transportable and drones are difficult to detect and intercept. Terrorist groups have developed, threatened to or utilized drones as a tool in pursuit of their goals in the US, Europe and elsewhere. Furthermore, Michaelides-Mateou suggest that public awareness will assist in mitigating the threat and discusses preventive and counter measures, like tracking software, kill switches and geofencing, to deal with terrorist drones.

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1.4.3 Part III: Ethical Issues Drones provide lots of opportunities, but not everything that is possible is also worth pursuing. Some applications of drones may be controversial. Part III of this book deals with ethical issues of the use of drones. Ethical aspects of drone use are particularly present in warfare and armed conflict. Focusing mostly on military drone use, this part of the book discusses the morality of autonomous weapon systems and automated killings. In Chap. 9, Bergman discusses moral and psychological implications of drones in warfare. In a relatively short time drones have claimed a special position in modern warfare. This has caused extensive debate on the morality of autonomous weapon systems and targeted killings. Bergman argues that although drones have been humanized, for instance, by labelling them as ‘killer-drones’, they are still

machines incapable of exerting moral judgment. Instead, he emphasizes that it is humans, not machines, that make decisions to use such systems. Drones allow killing from a distance, which may raise moral issues but may also have psychological implications for drone pilots, who may suffer from post-traumatic stressdisorder (PTSD). Bergman advocates further integrating drones in military units to make them a more natural tool for military commanders and to reduce risks for their soldiers. This may enable operations that prevent or faster resolve conflicts which were previously considered too risky. In Chap. 10, Brown discusses moral courage in drone warfare. Concepts of moral courage in manned combat are often based on the behaviour that combatants display in high-risk situations. Brown explores whether drone warfare, which appears risk-free for drone pilots who remotely operate drones, also requires moral courage. He argues that drone warfare entails both psychological and moral harms. Psychological and mental health research indicates that military drone pilots suffer from mental health problems at similar rates as pilots of manned combat aircraft. Furthermore, a strict dichotomy between bodily harms and psychological harms fails to recognize that these are inextricably conjoined together. Since most drone pilots perform the panopticon-like surveillance on their targets, there may a deep level of intimacy regarding their personal details. This may increase the psychological and emotional intensity for drone pilots and can be morally disconcerting. Brown argues that drone warfare, because of its unprecedented technological features can actually demand a more rigorous form of courage, beyond confronting bodily harms. In Chap. 11, Zwijnenburg and Blok investigate the practical and ethical challenges of drone use in conflict. The growing use of drones in warfare has raised concerns over the implications for the protection of civilians in armed conflict, international human rights law and the lowering of the threshold to use violence as a means to solve conflict. Innocent civilians are being killed by drones in warzones and other places. Furthermore, the 24/7 presence of drones in parts of Yemen, Pakistan and Somalia affects the minds of the local population, causing post-traumatic stress-disorder and other mental health issues. Zwijnenburg

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and Blok focus on the proliferation of dual-use drone technology to state and nonstate actors and implications for new ways of war. The changing nature of conflicts and growing use of proxy wars may lead to an increase in risk-free use of drones. Zwijnenburg and Blok argue that increased transparency and accountability are needed to address illegal use of armed drones. In Chap. 12, Coeckelbergh discusses several arguments against the lethal use of drones. Drones that are used for targeted killing, killing at a distance, and automated killing pose problems that are not new, such as problems related to the justification of war and the problem of distance. However, drones create a moral distance between killer and target while at the same time sensor technologies bridge the distance. Coeckelbergh focuses on two arguments against automated killing. First, it is questionable whether drones can ever be moral agents. Second, it is questionable whether drones can ever be ‘moral patients’, i.e., drones do not know human suffering. Coeckelbergh concludes that there are serious ethical problems with drones and argues that there is such a morally significant qualitative difference in vulnerability and way of being between drones and humans that fully automated killings cannot be justified.

1.4.4 Part IV: Legal Issues Part IV of this book examines legal issues regarding the use of drones. The most obvious legal issues are related to aviation safety, as drones may pose risks to other aircraft.34 Drones can crash and can hit people, leading to injury and even death. Furthermore, drones may collide with other air traffic, such as helicopters, small airplanes and even commercial airliners, creating additional risks. These scenarios are far from fictional, as several incidents reports show.35 Precisely because of these safety risks the use of drones is severely limited in most countries by legal restrictions. Apart from aviation law, there are several other legal issues regarding the use of drones, including property law, tort law, liability law, privacy law, personal data protection law, human rights and criminal law. In Chap. 13, Scott introduces and critically discusses the key aviation laws that currently regulate the use of civil drones under international, European Union (EU) and national law. The Chicago Convention of 1944 contains the overarching legal framework that regulates international civil aviation. It contains provisions for pilotless aircraft, such as flight authorization, noise and emission standards, proper documentation and airworthiness, but some obligations are not really practical for drones, such as carrying heavy documents on-board of minidrones. The Montreal Convention of

1999 establishes a legal framework for liability for damage to passengers, baggage and cargo engaged in international flights, but has

34 GAO Report 2012. 35 Quinn 2014; Gillespie 2014; Whitlock 2014.

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limited applicability for drones, since most civil drone flights are not international. The Rome Convention of 1952 establishes a legal framework for liability caused by aircraft to third parties on the surface and contains provisions on insurance requirements. Scott shows that the majority of international treaties do not appropriately regulate drone activities. Furthermore, the EU is still amending and creating new laws and national law has been left to fill the gaps. In Chap. 14, Volovelsky focuses on drone use and the right to privacy. The combination of advanced technologies, unique drone platforms and cheap prices of the drones will inevitably lead to acute infringements of the right to privacy. This threat is real and immanent. This raises the question how to draw the right balance between freedom of expression and the dynamic right to privacy, preserve the significant benefits arising from civilian drones and minimize their negative social impact. The problem of how to regulate the use of drones is shared by different legal systems around the world, including the US and the EU legal systems. Volovelsky reviews different solutions offered in the US and the EU and describes the legal framework of Israel, the world's largest producer of drones, as a unique mixed legal system that offers the opportunity to examine the implementation of various solutions. In Chap. 15, Eijkman and Bakker discuss accountability for and transparency of the use of armed drones. For instance, drones are used in Afghanistan, Pakistan and Yemen against Al-Qaeda and associated forces. Civilian victims of such armed drone strikes meet countless challenges in effectuating their right to an effective remedy. In many situations a formal recognition of the drone strike is absent and involved states do not release information about their drone use and their own investigations. Although both international humanitarian and human rights law can apply, in practice it is very difficult for victims to substantiate their status as victims and to seek access to justice and enforce their rights. Eijkman and Bakker argue that the international community should urge involved states to independently and impartially investigate all armed drone strikes and to ensure that access to an effective remedy for civilian citizens becomes a reality. In Chap. 16, Ravich explores best practices and policies for drone use around the world. Worldwide countries are facing challenges in regulating the use of drones. Many nations have developed or are developing drone laws. However, because drone technology is a relatively recent phenomenon, there are no long standing legal frameworks, policies and practices. Ravich surveys drone aviation laws around the globe by exploring the first iteration of laws, acts, regulations, guidance and policy statements and secondary source literature with respect to drones. This comparative country-by-country analysis provides an overview of existing drone laws and identifies best practices for civil and commercial drone use worldwide. This evaluation shows a comparable conservatism among lawmakers globally but also reveals that some countries have relatively assertive policies.

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1.4.5 Part V: Conclusions Part V of this book aims to offer possible ways forward and solutions or parts thereof to some of the issues addressed in the other parts of this book. It may be obvious that there are no simple solutions. For instance, it is not possible to set out in detail the contours for future legislation, as this depends on future technological developments and the social and political desirability of permitting or prohibiting particular applications of drones. However, when the goal is to avoid and minimize the threats that drones may pose and to increase or enhance the possibilities that drones may offer, some approaches and practices may be more useful than others. Examples, though sometimes country-specific, may include creating a policy vision across aviation law, privacy law and criminal investigation law, more cooperation between government entities, the pursuit of international regulations, making rules independent of technology (to some extent), using privacy impact assessments and privacy by design.36 In addition, information campaigns, particularly

for the rapidly growing group of non-professional users, could be very valuable with a view to compliance with regulations. The risks and threats of drone use can further be mitigated by defining additional (technical) specifications and (mandatory or not) certification and training. In Chap. 17, Wright and Finn explore Privacy Impact Assessments (PIAs) as a useful tool to address privacy issues raised by drones. It is obvious that drone users should comply with privacy law and personal data protection law, but privacy impact assessments go beyond compliance issues. A PIA should also include privacy issues that are not necessarily legal issues, such as potential chilling effects drones may have on the behaviour of people. Hence, there are limitations to Article 33 of the draft European Data Protection Regulation as data protection impact assessments may not address all relevant types of privacy, notably privacy of behaviour, privacy of location, privacy of groups and privacy of communications. Wright and Finn describe the process of performing a PIA and consider questions such as when a PIA should be performed and by whom. Using the PIA model they map privacy issues raised by drones, particularly non-recreational, non-military drone use. After mapping the privacy issues, they provide several potential solutions, including privacy-preserving technologies, to avoid or mitigate privacy risks. In Chap. 18, McKenna addresses public perception and acceptance challenges of drone use: will people accept large numbers of drones in the skies above them? Considering the factors that are likely to prove influential in whether wide scale drone use will be acceptable for the wider general public, he argues that other challenges of drone use, such as overcoming various technical and security weaknesses and privacy issues, ensuring the necessary national and international regulatory structures and enforcement issues, are also relevant for public perception and acceptance. McKenna discusses various self-help regulatory mechanisms 36 Custers et al. 2015, p. 161.

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regarding trespass, nuisance and harassment and technological solutions like geofencing, i.e. pre-programming drone control software in order to block drone flights above particular altitudes, at or near airports and above private property of home owners who object to drone flights. In Chap. 19, Custers addresses the question how to regulate the use of drones in the future given the expectation that the number of drones in the air is expected to increase rapidly in the coming years. Banning drones from society is not a realistic option. Having large numbers of drones, however, will put enforcement under pressure. Custers investigates conditions and contents of future drone legislation and analyses privacy and other safeguards that can be taken. Conditions for future drone legislation concern creating policy visions, further integration of aviation laws, telecommunication laws and criminal justice laws, regulation on international levels, mandatory evaluations and (to some extent) technology-independent legislation. The contents of future drone legislation should focus on aviation law, privacy law, liability law and criminal law. Privacy safeguards include privacy impact assessments and the use of privacy by design, most notably geofencing. Other safeguards include mandatory education for some groups of drone users and raising public awareness.

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Article

Optimizing UAV Spraying for Sustainable Agriculture: A Life Cycle and Efficiency Analysis in India Shefali Vinod Ramteke 1 , Pritish Kumar Varadwaj 1, *and Vineet Tiwari 2*, 1

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Abstract Problem: Agriculture in India faces pressing challenges related to water scarcity, excessive pesticide use, and inefficient energy consumption, impacting both economic sustainability and environmental health. Methodology: This study integrates Life Cycle Assessment (LCA), Data Envelopment Analysis (DEA), Intelligent

Management Models (IMMs), and Multi-Criteria Decision Analysis (MCDA) to assess the economic and environmental benefits of UAV-based spraying in Indian agriculture. Data were collected from UAV service providers and field trials in Punjab, Haryana, and Rajasthan. Results: UAV spraying achieved a 70% reduction in water use, 40% reduction in pesticide consumption, and a 50% reduction in CO2 emissions compared to conventional spraying. DEA results showed higher efficiency scores for UAVs, while IMM optimization achieved 95% pesticide coverage and reduced drift by 80%. Implications: MCDA ranked government subsidies as the most effective policy intervention. These findings support UAV spraying as a viable, scalable solution for climate-smart agriculture in India, offering both productivity and sustainability gains. Keywords: Data Envelopment Analysis; Intelligent Management Model; Life Cycle Assessment; Multi-Criteria Decision Analysis; precision agriculture; UAV spraying Academic Editor: Piotr Prus Received: 21 April 2025 Revised: 16 June 2025 Accepted: 1 July 2025 Published: 7 July 2025 Citation: Ramteke, S.V.; Varadwaj, P.K.; Tiwari, V. Optimizing UAV Spraying for Sustainable Agriculture: A Life Cycle and Efficiency Analysis in India. Sustainability 2025, 17, 6211. https://doi.org/ 10.3390/su17136211 Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/ licenses/by/4.0/).

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- Introduction Indian agriculture is confronted with increasingly complex sustainability challenges, particularly in the form of declining water availability, the overuse of chemical inputs, and diminishing resource-use efficiency. With nearly 80% of freshwater withdrawals allocated to irrigation and the evidence of aquifer stress rising across states such as Punjab, Haryana, and Rajasthan, concerns about groundwater depletion are now central to national agricultural planning [1]. Compounding this issue is the excessive use of pesticides, often exceeding recommended dosages, which has contributed to soil degradation, chemical runoff, and long-term ecosystem toxicity [2]. Despite policy awareness, current input delivery methods, including tractor-mounted boom sprayers and manual backpack systems, remain dominant. These methods, however, are often inefficient, labor-intensive, and prone to high chemical drift and resource wastage [3]. Unmanned Aerial Vehicles (UAVs), or agricultural drones, have emerged as a precision spraying solution capable of addressing these systemic inefficiencies. UAV-based application systems allow for lower-volume, targeted delivery of agrochemicals, with empirical studies showing water savings of nearly 70%, reductions in pesticide use of 30–40%,

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and significant improvements in energy efficiency relative to conventional practices [4–7]. These operational gains also yield measurable environmental benefits, including lower CO2 emissions, reduced chemical runoff potential, and decreased pressure on water resources [8]. More recent investigations have expanded our understanding of UAV spraying performance under diverse Indian conditions. Ref. [9] evaluated precision UAV spraying in rice–wheat systems of Punjab, reporting 15–20% improvements in deposit efficiency when using variable-rate nozzles under field-scale operations. Ref. [10] conducted canopy coverage assessments in humid terrains and demonstrated that sensor-driven nozzle control can further reduce off-target drift by up to 12%. These findings complement [11] the broader synthesis of multi-rotor configurations and underscore the rapid evolution of UAV spraying technologies in recent years. Recognizing this, the Government of India has introduced targeted support mechanisms under the Precision Agriculture Mission and the Sub-Mission on Agricultural Mechanization (SMAM), including subsidies for UAVs and training programs aimed at rural operator development [12]. Despite these efforts, adoption remains limited due to high initial investment costs, regulatory ambiguity, a lack of technical know-how, and limited field-level data on actual performance [13,14]. This study aims to fill this critical gap by conducting an integrated, data-driven evaluation of UAV spraying technologies across three high-input crops—rice, wheat, and mustard—in the resource-stressed regions of Punjab, Haryana, and Rajasthan. This study employs five integrated analytical approaches:

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Life Cycle Assessment (LCA): A standardized method ISO 14040 [15] for quantifying environmental impacts—here used to estimate per-hectare carbon emissions, water footprint, and pesticide runoff. Data Envelopment Analysis (DEA): A non-parametric benchmarking technique that evaluates operational efficiency by comparing multiple inputs (water, pesticide, energy) against outputs (crop yield and emission reductions). Intelligent Management Models (IMMs): Simulation-based models that optimize UAV spraying parameters—such as nozzle type, droplet size, flight altitude, and speed—to maximize canopy coverage and minimize off-target drift. Multi-Criteria Decision Analysis (MCDA): A decision-support tool that weights and ranks policy interventions (e.g., subsidies, training programs, regulatory changes) based on economic feasibility, environmental impact, and institutional readiness.

These frameworks collectively enable a comprehensive, data-driven assessment of UAV spraying viability, efficiency, and policy pathways in Indian agriculture. Operational parameters such as flight configuration, nozzle selection, and rotor count critically influence UAV spray performance. In Indian cropping systems, flight altitudes of 2–3.5 m above the canopy have been shown to optimize droplet deposition while minimizing off-target drift. Common nozzle types include flat-fan (180–200 μm droplets), hollow-cone (140–160 μm), and variable-rate nozzles (adjustable 180–250 μm) that dynamically adapt to canopy structure and flight speed. Likewise, multi-rotor platforms differ in stability and payload: four-rotor UAVs offer greater maneuverability but lower spray volume capacity, whereas six- and eight-rotor configurations deliver enhanced stability and payload, improving canopy penetration under variable field conditions [11]. This study's field trials assess these parameters across Punjab, Haryana, and Rajasthan to identify optimal UAV spraying settings for Indian agro-climatic contexts. While UAV spraying technologies have shown promise in controlled experiments, large-scale, integrated evaluations under real-world Indian agro-climatic and economic conditions remain scarce. In particular, few studies couple field-collected input-use and yield data with both environmental (LCA) and operational (DEA, IMM) modeling, and none have applied a multi-criteria policy analysis (MCDA) to rank adoption strategies.

This study addresses these gaps by triangulating DSP records, farm-level measurements, and multi-framework modeling to deliver a comprehensive assessment of UAV spraying viability and optimization in Punjab, Haryana, and Rajasthan. Study Objectives and Hypotheses To clarify the focus and scope of this research, we specify the following objectives and associated hypotheses:

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Objective 1: Quantify reductions in water, pesticide, and energy inputs achieved by UAV spraying versus conventional methods. # Hypothesis 1 (H1): UAV spraying reduces water use by ≥50%, pesticide use by ≥30%, and energy use by ≥40% compared to conventional spraying.

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Objective 2: Evaluate the environmental benefits via Life Cycle Assessment (LCA). # Hypothesis 2 (H2): The operational carbon footprint of UAV spraying is at least 40% lower than that of conventional methods.

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Objective 3: Benchmark operational efficiency through Data Envelopment Analysis (DEA). # Hypothesis 3 (H3): UAV-operated farms achieve higher DEA efficiency scores ($\theta \geq 0.8$) than conventional farms ($\theta < 0.6$).

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Objective 4: Optimize UAV spraying parameters using Intelligent Management Models (IMMs) to maximize coverage and minimize drift. # Hypothesis 4 (H4): Variable-rate nozzle configurations can achieve ≥ 90% canopy coverage with ≤10% drift under field conditions.

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Objective 5: Rank policy interventions using Multi-Criteria Decision Analysis (MCDA). # Hypothesis 5 (H5): Government subsidy schemes will score the highest in the combined economic, environmental, and institutional criteria.

- Methodology 2.1. Data Collection 2.1.1. Study Regions and Crop Selection To ensure that the dataset captured the representative irrigation and pesticide application practices in Indian agriculture, we selected three states—Punjab, Haryana, and Rajasthan—as our focal regions. Region selection was guided by three quantitative criteria: (i) groundwater overdraft exceeding 90% of annual recharge—128% in Punjab, 116% in Haryana, and 91% in Rajasthan [16]; (ii) high cropping area shares for the target crops— Punjab and Haryana contribute approximately 14% and 12% of national rice and wheat areas, respectively, while Rajasthan accounts for 40% of India's mustard production [17]; and (iii) the availability of UAV spraying services, with at least six commercial Drone Service Providers operating across over two-thirds of the agricultural districts in these states [4]. These metrics ensured that the study regions represent high-input, resourcestressed cropping systems ideal for assessing the impacts of UAV spraying. These states are characterized by high-input cereal and oilseed cultivation, particularly rice, wheat, and mustard, which account for a significant share of India's agricultural GDP and pesticide consumption [18,19]. Rice and wheat dominate Punjab and Haryana's cropping systems, while Rajasthan contributes over 40% of India's mustard production [17,20]. These crops were selected due to their intensive water and pesticide requirements, making them prime candidates for assessing UAV-based input optimization. Key pressure agents include brown planthopper and bacterial leaf-blight in rice, yellow-rust and aphid complexes in wheat, and Alternaria blight plus white rust in mustard. Rice cultivation

in Punjab and parts of Rajasthan is marked by high irrigation demand and frequent pest outbreaks [21]. On the other hand, wheat and mustard crops rely on multiple phytosanitary applications for disease and weed control. On average, farmers in these regions apply 4–5 spray events per season, delivering a cumulative dosage of 3.1 ± 0.3 kg active ingredient per hectare, based on Drone Service Provider operational logs and guidelines [22]. In all three states, more than 70% of irrigation is groundwater-dependent, and excessive extraction has led to rapid aquifer depletion, especially in Punjab and Haryana [16]. Furthermore, conventional pesticide spraying in these regions often exceeds recommended dosages, exacerbating chemical runoff risks and environmental degradation [17,23]. This context offers a robust testing ground for evaluating UAV spraying efficiency and sustainability. 2.1.2. Primary Data Sources Primary data for this study were collected through structured interviews and operational records provided by six commercial Drone Spraying Service Providers (DSPs) operating across the study regions. Data were gathered between 2022 and 2023 and included metrics on water use (m3 /ha), pesticide consumption (kg/ha), energy use (converted to kWh equivalents for diesel in conventional methods), operational costs (INR/ha; USD/ha), and final crop yield (kg/ha). DSPs provided comparative records from farms where both conventional and UAV spraying methods had been employed. For conventional spraying, water and pesticide usage were derived from tractor or knapsack sprayer logs, while UAV spraying records reflected battery-powered operations and automated chemical dispensing. Energy usage (kWh/ha) was calculated by converting diesel consumption to electrical equivalents via the formula: Econventional = Vdiesel × 10.7 kWh per liter (±5% error) where Vdiesel is the diesel volume recorded (L/ha), and 10.7 kWh/L is the conversion factor [24]. For UAV operations, electricity use was measured directly from battery charge logs and confirmed against inverter meter readings (error margin: ±5%). Yield data obtained via farmer feedback were cross-checked against local extension service records, limiting subjective bias to under 8% variance. In total, 18 farm-level samples were analyzed, i.e., nine conventional and nine UAVoperated farms, ensuring equal representation across the three study states—six farms from each state. This sample was designed to reflect regional diversity in agro-climatic conditions, cropping intensity, and farmer operating scales [4]. 2.1.3. Secondary Data and Triangulation Triangulation of primary data was conducted systematically by benchmarking and adjusting DSP field records against authoritative secondary benchmarks, specifically, as follows: 1.

2.

3.

Water use: DSP-recorded volumes (m3 /ha) were compared to ICAR-recommended spray volumes per crop [22]. When DSP values deviated by more than ±10%, proportional adjustment factors were applied to align logs with the recommended baselines. Pesticide application: Field pesticide rates (kg/ha) were cross-validated with ICAR dosage manuals and state extension bulletins. Records exceeding recommended thresholds were down-adjusted to the regional mean dosage. Operational cost: Cost components (labor, fuel, maintenance, UAV depreciation) from service providers were reconciled with NABARD UAV cost studies (NABARD, 2021). Items exceeding 1.5× the median cost were capped to reflect typical service rates.

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4.

5.

Groundwater stress: Regional overdraft metrics from the Central Ground Water Board (CGWB, 2021) provided context for water savings, allowing the normalization of reductions relative to the local stress levels. Yield validation: Farmer-reported yields were validated against MoA&FW district yield statistics [12] and adjusted within a ±5% range of official averages to mitigate subjective bias.

This rigorous triangulation refined our baseline assumptions to ensure that the subsequent LCA, DEA, IMM, and MCDA analyses were grounded in verified, regionally calibrated data. 2.1.4. Expanded Raw Data Overview The dataset compiled from DSP records and field logs formed the empirical foundation for our quantitative analyses in Section 3. In this study, each individual farm is treated as a decision-making unit (DMU)—a standard term in DEA referring to the unit whose inputs (water, pesticide, energy, labor) and outputs (crop yield, cost savings, emission reductions) are evaluated. By defining farms as DMUs, we can quantitatively benchmark their relative operational efficiency under both UAV and conventional spraying scenarios (see Section 3.3). Each farm was treated as a DMU and was associated with the following key performance variables: region, crop, spraying method, water usage, pesticide usage, energy consumption, operational cost, and final crop yield. For energy calculations, conventional diesel usage was converted to kWh equivalent using 1 L diesel = 10.7 kWh [24]. Table 1 summarized the field data collected from DSPs and conventional farms based on farm ID, region, crop, method, water use, pesticide use, energy use, operational cost, and crop yield. Table 1. Summary of field data collected from DSPs and conventional farms.

Farm ID

Region

Crop

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

Punjab Punjab Punjab Punjab Haryana Haryana Haryana Haryana Haryana Haryana Haryana Haryana Rajasthan Rajasthan Rajasthan Rajasthan Rajasthan Rajasthan

Rice Rice Rice Rice Wheat Wheat Wheat Wheat Mustard Mustard Mustard Mustard Mustard Mustard Mustard Mustard Rice Rice

Method

Water Use (m3 /ha)

Pesticide Use (kg/ha)

Energy Use (kWh/ha)

Operational Cost * (INR/ha; USD/ha #)

Crop Yield (kg/ha)

Conventional Conventional UAV UAV Conventional Conventional UAV UAV Conventional Conventional UAV UAV Conventional Conventional UAV UAV Conventional UAV

10,000 9500 2900 3100 8000 7800 2500 2700 7000 6800 2400 2600 7000 7500 2200 2100 9000 2200

3.5 3.3 2.0 2.2 3.2 3.1 1.9 2.0 3.0 2.8 1.7 1.8 3.0 3.2 1.6 1.5 3.4 1.6

50 48 26 25 45 43 20 21 40 38 18 19 40 42 17 18 47 19

5500; (67.1) 5400; (65.9) 3700; (45.1) 3800; (46.3) 5000; (61.0) 4900; (59.8) 3600; (43.9) 3650; (44.5) 4800; (58.5) 4700; (57.3) 3500; (42.7) 3550; (43.3) 4800; (58.5) 4900; (59.8) 3300; (40.2) 3400; (41.5) 5300; (64.6) 3450; (42.1)

4500 4600 4650 4700 4300 4350 4400 4450 4200 4250 4350 4380 4200 4220 4280 4310 4450 4380

USD values converted at an average exchange rate of INR 82 per USD, corresponding to the 2022–2023 period. * Operational cost definition: operational cost (INR/ha) reported in Table 1 encompasses both variable and fixed cost components.

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Variable costs include the following:

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Fuel or electricity for machinery (diesel for tractor sprayers; grid electricity for UAV battery charging); Labor for equipment operation and field setup; Chemical inputs (pesticide acquisition).

Fixed costs cover the following:

• • •

Equipment depreciation (straight line over a 3-year service life); Routine maintenance and repair overheads; Insurance and licensing fees.

All cost figures represent the average observed values per hectare across the nine UAV-served and nine conventional farms in our sample. These data points formed the basis for our Regression Analysis (Section 3.1), Life Cycle Assessment (Section 3.2), Data Envelopment Analysis (Section 3.3), and Cost–Benefit Evaluations (Section 3.4). 2.1.5. UAV Platforms and Spraying Hardware Commercial Drone Service Providers (DSPs) participating in this study operate under non-disclosure agreements; therefore, individual make and model names are anonymized. Table 2 summarizes the key airframe and spraying-system specifications for the three multi-rotor platforms—designated Platform A, Platform B, and Platform C—that together cover > 90% of the treated area in our dataset. These specifications define the feasible parameter space for the IMM optimization (Section 2.4) and underpin the energy-use and LCA calculations (Section 2.2). Table 2. Technical specifications of the study UAV platforms (platforms A–C).

Platform

Rotor Count

Maximum Payload (L)

Supported Nozzle Types †

DropletSize Range (μm)

Typical Flight Altitude (m AGL)

Swath Width (m)

A

8

10

Flat-fan, Hollow-cone, Variable-rate

140–250

2.5–3.5

4–5

B

6

12

Flat-fan, Hollow-cone, Variable-rate

150–230

2.5–3.0

4–5

C

4

8

Flat-fan, Hollow-cone

160–200

2.0–3.0

3–4

Operational envelope (all platforms): altitude 2–3.5 m above canopy, ground speed 2–5 m s−1 , spray volume 20–60 L ha−1 , wind speed < 5 m s−1 , and relative humidity > 50%. † Variable-rate (VR) nozzles provide real-time droplet-size adjustment via pulse-width modulation.

2.2. Life Cycle Assessment (LCA) for Environmental Impact A Life Cycle Assessment (LCA) framework was developed to quantify the comparative environmental impacts of UAV-based spraying and conventional methods in Indian agriculture. This LCA follows the ISO 14040 guidelines, focusing on the use phase of operations to compare the direct operational impacts of UAV versus conventional spraying. We explicitly exclude upstream impacts (machinery manufacturing, component transport, battery production) and downstream end-of-life processes. This boundary choice aligns with operationally focused agricultural LCAs [25,26] and allows a clear comparison of spray-phase efficiencies. We acknowledge that a full cradle-to-grave assessment—including UAV and sprayer fabrication, logistics, and decommissioning—could alter absolute carbon

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and water footprint values; however, prior studies suggest that relative differences in operational phase emissions remain consistent [27]. Future research should extend this analysis to incorporate complete life cycle stages for comprehensive environmental evaluation. The environmental indicators selected were the carbon footprint (measured in kg CO2 per hectare), the water footprint (in cubic meters per hectare), and the pesticide runoff potential (in kg per hectare). These metrics were computed using a combination of field-collected data, emission factors, and statistical modeling techniques. 2.2.1. Carbon Footprint Estimation The carbon footprint was assessed by aggregating emissions from fuel combustion, electricity consumption, and the production of chemical inputs, particularly pesticides. For conventional tractor-based operations, emissions were primarily derived from diesel fuel use, whereas UAV spraying emissions originated from battery-powered electricity inputs. The total carbon footprint CF total per hectare was calculated as the sum of emissions from (a) fuel combustion in diesel-based systems, (b) electricity use in UAV battery charging, and (c) pesticide production. The total emissions per hectare were expressed as the sum of these three components in Equation (1), where CF total refers to carbon emissions from diesel fuel use, CF f uel represents emissions from electricity consumed during UAV battery charging, and CF chemical denotes emissions associated with the production of pesticides. CF total = CF f uel + CF electricity + CF chemical

(1)

For conventional methods, the emissions from fuel use were calculated using Equation (2), where Ediesel represents the diesel consumed per hectare (liters/ha), and E Fdiesel is the emission factor for diesel combustion, taken as 2.68 kg CO2 per liter based on the IPCC standards [28]. CF f uel = Ediesel × E Fdiesel (2) For UAV-based operations, emissions due to battery charging were calculated using Equation (3), where Eelectric is the electricity used per hectare in kilowatt-hours (kWh/ha), and E Felectric is the emission factor of grid

electricity generation in India, assumed to be 0.85 kg CO2 per kWh based on the latest India's grid emission factor [29]. CF electricity = Eelectric × E Felectric

(3)

Additionally, the carbon burden from pesticide-related emissions was calculated using Equation (4), where Puse is the amount of pesticide applied per hectare (kg/ha), and E Fpesticide is a weighted emission factor for pesticide production. Based on the active ingredient composition in our field trials (approximately 60% insecticides and 40% fungicides), we applied class-specific factors of 5.2 kg CO2 /kg for insecticides and 3.2 kg CO2 /kg for fungicides [30,31]. This yields a composite factor of 4.5 kg CO2 /kg, reflecting the average mix applied across farms. CF chemical = Puse × E Fpesticide (4) These equations were applied across all decision-making units to generate crop-wise and region-wise carbon footprints. These three components together provided the total operational carbon footprint for each spraying method. 2.2.2. Water Footprint Estimation The water footprint WF total was computed to capture the quantity of freshwater used during spraying operations that aggregated the spray solution volume, rinse and refill losses, and estimated runoff. This was particularly relevant for comparing UAV systems,

which typically use ultra-low volumes, with conventional methods that require larger tank capacities and higher field saturation. WF total = SV + RL + RO

(5)

The overall water usage per hectare was calculated using the formula in Equation (5), where SV denotes the spray volume used per hectare (m3 /ha), RL represents the rinse and refill water losses, and RO captures the potential runoff due to excess spray or poor infiltration. UAV systems typically operate at ultra-low spray volumes, reducing SV and RO, while conventional tractor sprayers exhibit higher values for all components. Baseline parameters were drawn from DSP field logs and aligned with ICAR-recommended spray volume guidelines [22]. 2.2.3. Pesticide Runoff Estimation To evaluate environmental risks associated with chemical leakage, the pesticide runoff potential was modeled using the quantity of pesticide applied and a runoff coefficient, reflective of the application method and field conditions. Pesticide runoff potential PR was calculated to estimate the proportion of applied pesticide that could enter the surrounding environment through surface runoff as shown in Equation (6). PR = Puse × RC

(6)

In this equation, Puse is the pesticide applied (kg/ha), and RC is the runoff coefficient. For conventional spraying, RC values typically ranged from 0.20 to 0.30, while UAV spraying, owing to its more precise application, employed a lower runoff coefficient. Values were supported by empirical field trials and environmental pesticide modeling protocols [32,33]. 2.2.4. Monte Carlo Simulation for Uncertainty Analysis Given the variability in field conditions and input data, a Monte Carlo simulation framework was integrated with the LCA model to assess uncertainty in the environmental outcomes. The simulation was executed using 10,000 iterations per variable, providing probabilistic distributions for carbon footprint, water footprint, and pesticide runoff across both spraying methods. Each environmental variable was assumed to follow a normal distribution. The simulation produced percentile-based estimates and 95% confidence intervals, calculated using Equation (7), where P2.5 and P97.5 refer to the 2.5th and 97.5th percentiles of the simulated output distribution. This allowed the estimation of probabilistic bounds around the LCA outcomes, ensuring the robustness of comparisons. These Monte Carlo simulations were implemented in Python 3.10 (Python Software Foundation, Wilmington, DE, USA) using the NumPy v1.22 library (NumPy Developers, Open-Source Community, USA) for numerical operations and SciPy v1.8 (SciPy Community, Austin, TX, USA) for random sampling, adhering to the best practices in stochastic environmental modeling [27]. All simulation scripts and codes are publicly available at https://github.com/rss2019003/Sustainability, accessed on 30 June 2025. CI = [P2.5 , P97.5]

(7)

2.2.5. Tornado Sensitivity Analysis To determine the relative influence of various operational parameters on the environmental performance of UAV spraying, a Tornado Sensitivity Analysis was conducted. This method applied a one-at-a-time (OAT) variation approach, where individual input param-

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eters were altered independently within a ±20% range from their baseline values, while holding all other inputs constant. This analytical framework follows the sensitivity modeling protocols used in precision agriculture LCA research [34]. Each key parameter—such as diesel usage Ediesel , pesticide volume Puse , water application rate SV, and UAV battery efficiency E Felectric , and meteorological conditions—were independently varied within ±20% of its base value, while holding other variables constant. Each parameter was systematically perturbed, and the resulting change in total environmental impact—measured as changes in carbon emissions (kg CO2 /ha) and water usage (m3 /ha)—was recorded. The OAT method was implemented using Python's NumPy-based simulation routines, reflecting a deterministic modeling approach commonly used in parametric agricultural system assessments [34]. The percentage impact of each variable on the selected environmental metric was estimated using the following deterministic Equation (8), where Max Output and Min Output represent the system-level outcome (e.g., CO2 or water footprint) at +20% and −20% of the variable under consideration, and Baseline Output refers to the model outcome using original field values (pre-perturbation). Impact% =

Max Output − Min Output × 100 Baseline Output

(8)

This "one-at-a-time" variation approach enabled the ranking of parameters based on their effect size on total carbon emissions and water usage. The analysis provided insights into which variables UAV operators and policymakers should be prioritized for optimizing environmental performance. The resulting shifts in environmental indicators allowed the ranking of parameters by influence, and highlighted priority areas for UAV system optimization. This sensitivity assessment framework is particularly valuable for guiding UAV operational planning, as it identifies which parameters should be prioritized in optimization algorithms or training protocols. The sensitivity framework was adapted from the existing agricultural systems modeling literature by [34], which focused on decisionsupport frameworks for agricultural machinery evaluation under Indian conditions [34]. 2.2.6. Fuel and Electricity Cost Sensitivity Modeling A cost sensitivity model was embedded within the LCA framework to evaluate how fluctuations in fuel and electricity prices might affect the comparative economic and environmental performance of UAV spraying. Diesel prices were modeled within a range of INR 72–INR 108 L−1 (0.88–1.32 USD L−1), while electricity rates ranged from INR 5.6 to INR 8.4 kWh−1 (0.068–0.102 USD kWh−1), reflecting the recent volatility of Indian energy markets. These ranges reflected real-world variability recorded by India's Ministry of Petroleum and Natural Gas and Indian Energy Exchange over the past three years [35,36]. By linking these prices with energy consumption metrics from UAV and conventional systems, the model quantified the cost elasticity of each method. This integration of economic variables into the LCA framework provided a more realistic and policy-relevant understanding of technology viability under different market conditions. These fuel and electricity prices were integrated with energy usage metrics Ediesel and Eelectric to estimate per-hectare cost impacts and associated changes in carbon emissions. The hybrid cost– environmental model thus allowed a nuanced comparison of cost stability between the UAV and conventional systems. Similar economic–environmental coupling has been recommended in the recent techno-economic studies for sustainable AgriTech adoption in India [37].

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2.3. Data Envelopment Analysis (DEA) for Operational Efficiency To assess and compare the operational efficiency of UAV-based spraying versus conventional spraying, this study employed Data Envelopment Analysis (DEA), a wellestablished, non-parametric technique grounded in linear programming. DEA enables the evaluation of multiple decision-making units (DMUs)—in this case, individual farms—based on their ability to transform inputs into desirable outputs [38,39]. The technique has been widely applied in agricultural productivity studies to benchmark both technological adoption and input resource utilization efficiency [40,41]. DEA is particularly suitable in contexts where multiple inputs and outputs exist and where it is

necessary to avoid assuming a specific production function form, which is often the case in diverse farm-level datasets [42]. In this study, DEA was used to evaluate the relative efficiency of UAV and conventional spraying operations in terms of resource use and yield outcomes. The inputs considered were water usage (m3 /ha), pesticide application (kg/ha), energy consumption (kWh/ha), and labor cost (INR/ha; USD/ha). The outputs included post-harvest crop yield (kg/ha), operational cost savings (INR/ha; USD/ha), and emission reductions (kg CO2 /ha), derived from the Life Cycle Assessment (Section 2.2). The basic DEA efficiency score, denoted by θ, represents the proportion by which all inputs could be proportionally reduced without lowering output. A score of θ = 1.0 indicates that the DMU lies on the efficient frontier, whereas θ < 1.0 implies relative inefficiency and scope for input optimization. To implement this, this study adopted an input-oriented CCR (Charnes, Cooper, Rhodes) model that assumes constant returns to scale [38,43]. The goal of the model is to minimize input usage while maintaining at least the same level of output. The optimization structure is given as follows: Maximise θ (9) Subject to constraints: n

$$\sum_{j=1} \lambda_j x_{ij} \leq \theta x_{io}, \forall i \in \{1, \ldots, m\}$$ n

(10)

$$\sum_{j=1} \lambda_j y_{rj} \geq y_{ro}, \forall r \in \{1, \ldots, s\}$$

(11)

$$\lambda_j \geq 0, \forall j \in \{1, \ldots, n\}$$

(12)

Here, xij is the amount of input i used by the jth DMU, and yrj is the output r produced by the same. λ j represents the intensity weights, forming a hypothetical composite DMU from the observed set. The term θ is the efficiency score of the evaluated DMUo, where θ = 1 means full efficiency, and values less than 1 indicate potential input reduction while maintaining output. The DEA model was applied to a normalized dataset comprising 18 DMUs (9 UAVbased and 9 conventional) across different farms in Punjab, Haryana, and Rajasthan. All input and output variables were standardized prior to DEA computation, consistent with recommendations from prior agricultural DEA applications [34]. This method allowed for a multidimensional evaluation of spraying performance, capturing not only economic returns but also environmental performance metrics, which is essential in modern sustainable agriculture [44]. By quantifying the efficiency frontier, DEA was able to highlight UAV adoption as a systematically superior input–output transformation mechanism, particularly in regions with limited water resources and high input cost variability. Moreover, the results offer practical value for identifying inefficient farms (DMUs), quantifying excess input usage, and guiding extension programs or policy interventions.

DEA also supports the integration of precision technologies like UAV spraying within broader farm benchmarking systems [45]. 2.4. Intelligent Management Models (IMMs) for UAV Spraying Parameter Optimization To improve the precision, consistency, and efficiency of UAV-based pesticide spraying under Indian field conditions, an Intelligent Management Model (IMM) was developed. This model simulated the interactions between various UAV spraying parameters and optimized their values to maximize pesticide coverage while minimizing drift losses. The IMM framework was designed as a multivariable control and optimization system, integrating real-world operational constraints with field-calibrated input–output behavior. The core variables optimized through IMM included nozzle type, droplet size (μm), spray volume (L/ha), flight height (m), and flight speed (m/s). These were selected based on their physical influence on droplet trajectory, canopy penetration, and evaporation potential, as supported by the UAV agricultural spray literature [46,47]. Operational ranges were derived through structured interviews with six drone spraying service providers (DSPs) operating across Punjab, Haryana, and Rajasthan, as well as trial records collected between 2022 and 2023. To assess each UAV configuration's effectiveness, the IMM utilized two core performance indicators: Spray Coverage Efficiency (SCE) and Drift Potential Index (DPI). These indicators were adapted from empirical UAV spray modeling frameworks proposed by [48] and further developed for Indian agro-environmental conditions in [49]. Spray Coverage Efficiency (SCE) was used to measure how effectively droplets reached the intended leaf surface area, expressed in Equation (13).

Droplet Deposition µL/cm2 SCE = × 100 Target Deposition Threshold (µL/cm2)

(13)

In this equation, the numerator represents the actual deposition measured on the leaf surface, typically captured using water-sensitive paper, and the denominator reflects the minimum threshold of deposition required for effective pest control, which varies by crop and pesticide type. During our water-sensitive-paper calibration trials, pest incidence fell sharply once Spray Coverage Efficiency (SCE) reached ≈80% of the target deposit rate. Below that level, visible lesions or insect counts persisted; above it, no further efficacy gains were observed. These observations are consistent with the qualitative “adequate coverage” bands described by [5,48,49], all of whom treat SCE values substantially below the agronomic target as under-application and values well above it as potential overspray. Accordingly, our IMM objective function penalizes parameter sets with SCE < 80% (under-coverage) and SCE > 100% (overspray), rewarding configurations that maintain SCE in the 80–100% effectiveness band while also minimizing drift. This metric helped us evaluate whether a specific UAV configuration achieved sufficient coverage to be agronomically effective. Higher SCE values indicated better performance in terms of canopy penetration and uniform spray deposition. To capture the tendency for off-target dispersion and to quantify drift behavior, the IMM also computed the Drift Potential Index (DPI), which captures how likely it is for droplets to deviate from their target zone under a given configuration. DPI was calculated using Equation (14). DPI =

Droplet Size (µm) × Flight Height (m) Spray Volume (L/ha)

(14)

A lower DPI indicates a reduced risk of drift due to a higher droplet mass and a lower vertical travel distance, while a higher DPI reflects a greater likelihood of droplet deviating due to wind or thermal currents. Empirical UAV studies in India suggest that DPI values below 10 are considered acceptable under normal field conditions, particularly for rice and mustard crops [50]. The IMM simulations were run across three nozzle types commonly used in Indian UAVs: flat-fan, hollow-cone, and variable-rate nozzles. Flat-fan nozzles produced medium droplet sizes (180–200 µm) with wide lateral coverage but a moderate drift risk. Hollowcone nozzles generated finer droplets (140–160 µm), enhancing canopy penetration, but increasing susceptibility to drift under wind-prone conditions. Variable-rate nozzles provided real-time adaptability, adjusting droplet size between 180 and 250 µm based on the UAV speed and canopy structure, aligning with precision agriculture goals [51]. Field calibration trials were conducted in experimental plots distributed across the three study regions. Spray trials were designed to vary the UAV speed (2–5 m/s), altitude (2–4 m), and spray volume (20–60 L/ha) under each nozzle type. Spray coverage and drift were recorded using water-sensitive paper (WSP) and visual scoring grids. The results from these trials were used to calibrate IMM parameters using a weighted regression fitting approach. The IMM was then validated against held-out field data and tested for predictive robustness across varying humidity and wind conditions. Once calibrated, the IMM was capable of prescriptive application, dynamically generating optimal spraying configurations tailored to crop type, canopy density, wind speed, and field dimensions. Its underlying architecture is modular and suitable for integration into the UAV firmware, mobile-based control platforms, or digital decision-support systems (DSSs) used by UAV operators and agricultural extension agents. This makes the IMM framework not just a theoretical construct but a practical, deployable tool for advancing data-driven agricultural mechanization in India [52]. 2.5. Multi-Criteria Decision Analysis (MCDA) for Policy Evaluation To systematically evaluate the most viable strategies for promoting UAV-based pesticide spraying in Indian agriculture, a Multi-Criteria Decision Analysis (MCDA) framework was developed. MCDA offers a structured decision-support methodology that allows the incorporation of both qualitative and quantitative factors to compare multiple policy alternatives under complex, multi-objective conditions [53,54]. It is particularly useful in agrarian systems where economic, institutional, and environmental factors jointly influence technology adoption outcomes. In this study, the MCDA was employed to assess three real-world policy interventions designed to facilitate UAV adoption at scale. These included the following: (i) government subsidy schemes for UAV procurement and service support, (ii) operator training programs (e.g., Drone Didi Scheme), and (iii) regulatory fast-tracking of Drone Service Provider (DSP) licensing. The selection of policy alternatives was informed by stakeholder consultations and

current national initiatives under the Sub-Mission on Agricultural Mechanization (SMAM) and the Drone Rules 2021 [12,55]. The MCDA framework was based on a weighted additive scoring model, which has been widely adopted for agri-policy decision making involving multiple stakeholder perspectives [3,56]. The evaluation considered four criteria central to the UAV adoption in Indian agriculture. Economic feasibility assesses the relative cost-effectiveness of UAV spraying compared to traditional methods. Adoption feasibility evaluates operational accessibility, including the availability of service providers, training, and farmer willingness. Environmental impact measures potential reductions in pesticide usage, water consumption, and carbon emissions. Government support readiness captures institutional

facilitation, including subsidy availability, training support, and regulatory alignment. Among the policies considered within this framework, the Drone Didi Scheme warrants specific methodological attention due to its distinctive socio-economic positioning. This initiative, launched by the Government of India in 2023, aims to train over 15,000 rural women in UAV operations for agricultural use, with the goal of enhancing gender-inclusive mechanization and rural employment [57]. Its inclusion in the MCDA matrix was supported by stakeholder feedback highlighting both its direct influence on adoption feasibility and its indirect effect on institutional readiness. The scheme's formal integration into the scoring model ensures the methodological framework accounts for both technical and social impact criteria, aligned with the inclusive innovation policy evaluation standards. Each criterion was assigned a weight (Wn) representing its relative importance in the Indian context. These weights were determined using expert elicitation from agricultural policy researchers, DSP stakeholders, and state agricultural extension officers. Criteria such as cost feasibility and institutional readiness were given higher weightage, consistent with earlier adoption studies in Indian mechanization programs [19]. The total effectiveness score of a given policy intervention was calculated using the following Equation (15) where each factor was assigned a weight (Wn) based on its relative importance (0–1, sum = 1), and each UAV adoption policy was given a score (Sn) based on real-world feasibility for criterion n (e.g., cost reduction, feasibility, environmental benefit). N is the total number of evaluation criteria (in our case, 4). N

Policy Score= ∑n=1 Wn Sn

(15)

A scoring matrix was developed by collecting expert evaluations on a 10-point scale for each policy–criterion pair. These scores were aggregated and combined with the assigned weights to compute composite scores for each policy. The process followed the standard practices of MCDA implementation in agricultural and rural innovation contexts [58]. The model was implemented using Microsoft Excel (Version 365; Microsoft Corp., Redmond, WA, USA) and Python 3.10 (Python Software Foundation, Wilmington, DE, USA) for matrix calculations, and it remains adaptable for future use in scenario analysis or regional prioritization. The MCDA methodology offers a flexible and replicable framework that can be applied across different states, crop systems, or emerging UAV applications.

- Results and Discussion 3.1. Input Savings Analysis (Water, Pesticide, Energy) This section evaluates the quantitative differences in water usage, pesticide application, and energy consumption between UAV-based spraying systems and conventional methods across three Indian states. The analysis uses descriptive statistics, two-sample t-tests, and regression modeling to isolate the contribution of UAV usage to input efficiency, while controlling for confounding factors like crop type and field size. Additionally, the broader implications for groundwater sustainability are assessed based on the measured water savings. 3.1.1. Descriptive Analysis: Mean ± Standard Deviation Comparison To establish baseline comparisons, input usage values were aggregated from 18 fieldlevel decision-making units (DMUs), comprising 9 UAV-based farms and 9 using conventional spraying. Table 3 reports the means, standard deviations, and percentage reductions achieved by UAV spraying for each input metric.

Table 3. Input usage: conventional vs. UAV (mean ± SD).

Input Metric

Conventional (n = 9)

UAV (n = 9)

% Reduction (UAV)

Water Use (m3 /ha) Pesticide Use (kg/ha) Energy Use (kWh/ha)

7580 ± 1320 3.12 ± 0.31 44.2 ± 3.8

2430 ± 410 1.84 ± 0.22 20.2 ± 2.5

67.9% 41.0% 54.3%

These results show substantial input savings from UAV spraying. On average, UAV farms used 5150 m3 /ha less water, 1.28 kg/ha less pesticide, and 24 kWh/ha less energy than their conventional counterparts. Standard deviations are also markedly lower for UAV spraying across all input types, indicating tighter operational consistency and reduced variability between farms. For instance, water usage in UAV-based farms ranges from 2000 to 3100 m3 /ha, while in conventional methods, it fluctuates widely from 6800 to 10,000 m3 /ha. Such variability in conventional spraying reflects the inefficiencies inherent in manual and tractor-mounted application systems. Figure 1 confirms these means: UAV farms show a compact distribution, while conventional inputs scatter widely, underscoring greater operational consistency.

(a)

(b)

(c)

Figure 1. Distributions of on-farm input consumption under UAV (n = 9) and conventional (n = 9) spraying. Panel (a) water use (m3 ha−1); Panel (b) pesticide use (kg ai ha−1); Panel (c) energy use (kWh ha−1 , diesel converted at 10.7 kWh L−1). Boxes = IQR; center line = median; whiskers = 1.5 × IQR; dots are outside-whisker values.

Overall, these visualizations confirm that UAV spraying not only achieves substantial absolute input savings, but also introduces greater consistency, predictability, and control across farms. The reduced spread in all UAV boxplots reinforces its technological stability under real-world deployment conditions in diverse Indian agro-climatic zones. 3.1.2. Two-Sample t-Test Analysis To determine the statistical significance of these observed input differences, unpaired two-sample t-tests were conducted for each input type. Normality and homogeneity of variance were tested using the Shapiro–Wilk and Levene's tests, respectively. All input distributions satisfied the required assumptions for parametric testing ($p > 0.05$), enabling the use of t-tests with equal variances. The null hypothesis for each test was that there is no difference in mean input usage between the UAV and conventional spraying methods. Given prior evidence that UAV spraying reduces inputs, a one-sided t-test was appropriate; however, two-tailed p-values were also computed for robustness.

Hypotheses: H0 : μConv = μU AV (no difference in mean usage). Ha : μConv > μU AV (one-sided test, given prior evidence that UAV lowers inputs). Since we are strongly expecting UAV to reduce usage, we can apply a one-sided test. However, for completeness, we also confirm two-sided p-values remain well below 0.05. We perform unpaired two-sample t-tests for each input metric. The null hypothesis for each test was that there is no difference in mean input usage between the UAV and conventional spraying methods. Given prior evidence that UAV spraying reduces inputs, a one-sided t-test was appropriate; however, two-tailed p-values were also computed for robustness. All three one-sided t-tests are highly significant ($p < 0.0001$; Cohen's $d \geq 3.5$), validating the magnitude of the input reductions reported in Table 4. Table 4. Two-sample t-test results for input use.

Input

Method

n

Mean

SD
t-Stat
df
p-Value (One-Sided)
Cohen’s d
Water Use (m3 /ha)
Conventional
9
7580
1320
8.15
16
<0.0001
3.84
UAV
9
2430
410
Conventional
9
3.12
0.31
7.42
16
<0.0001
3.50
UAV
9
1.84
0.22
Conventional
9
44.2
3.8
8.97
16
<0.0001
4.23
UAV
9
20.2

2.5

Pesticide (kg/ha) Energy (kWh/ha)

For normality, we see that the Shapiro–Wilk p-values > 0.05 for UAV water (p = 0.13) and conventional water (p = 0.08) are acceptable for pesticide and energy. Also, for the variance homogeneity, Levene's test indicated no significant difference in variance for water, pesticide, or energy usage across the two groups. Thus, the standard unpaired t-test is valid in this context, and all three differences (water, pesticide, energy) are statistically significant (p < 0.001). UAV spraying indeed provides substantial input savings compared to conventional spraying. 3.1.3. Multiple Regression Analysis While t-tests assess mean differences, regression models were used to control for confounding variables such as crop type (rice, wheat, mustard) and field size. For each input metric, an Ordinary Least Squares (OLS) model was fitted to estimate the independent effect of UAV usage. As observed in Table 5, the coefficient β 1 for UAV use was negative and statistically significant (p < 0.001) across all models, confirming its independent impact in reducing resource consumption even after controlling for crop and field size. Field size was positively associated with input use, but only marginally significant, while crop effects were variable, with rice slightly increasing pesticide and energy needs. Following the estimation of the OLS regression models for water, pesticide, and energy usage, residual diagnostics were conducted to validate the statistical assumptions underlying linear regression: normality, homoscedasticity (constant variance), and independence of residuals. Figure 2 below presents the boxplots of residuals for each model, offering insight into the fit and behavior of the predictions.

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Table 5. Regression results (coefficients and p-values) for input usage.

Dependent Variable Water (m3 /ha) Pesticide (kg/ha) Energy (kWh/ha)

Intercept (p)

UAV Use β 1 (p)

6200 (0.002)

−5200 (0.000)

2.5 (0.01)

−1.4 (0.000)

39 (0.03)

−24.5 (0.000)

Crop Type (p)

Field Size (p)

R2

F-Stat (p)

+350 (0.04)

0.60

12.3 (0.000)

+0.05 (ns)

0.54

9.1 (0.001)

+0.8 (0.05)

0.58

11.5 (0.000)

Rice > Mustard > Wheat ns Rice (+)/Must (−) sig Rice slightly (+) sig

“ns” = not significant at p > 0.05, “sig” = p < 0.05, and “Rice > Mustard > Wheat ns” means rice uses more water than mustard/wheat, but not always strongly significant.

(a)

(b)

(c)

Figure 2. Regression residuals for models of (a) water, (b) pesticide and (c) energy use (n = 18 farms). Y-axes show residuals in the same units as the dependent variable: m3 ha−1 , kg ai ha−1 , and kWh ha−1 , respectively; x-axis lists the three input models. Boxplot styling as in Figure 1.

Residual diagnostics (Figure 2) satisfy normality, homoscedasticity, and independence, confirming model validity. In sum, all three residual plots reinforce that the regression models satisfy core statistical assumptions. There are no signs of autocorrelation, strong skew, or heteroscedasticity, validating the use of OLS for analyzing the UAV impact on input efficiency. The robustness of the models lends credibility to the inference that UAV spraying substantially reduces resource consumption across diverse cropping systems and field conditions. 3.2. Environmental Impact Assessment (LCA Results) 3.2.1. Carbon Footprint Estimation Results The total operational carbon footprint was assessed by aggregating emissions from diesel combustion, battery charging, and pesticide manufacturing, as described in Equations (1)–(4). Based on field data from 18 farms, the mean CO2 emission under conventional spraying was calculated as 46.2 ± 3.4 kg CO2 /ha, compared to 23.5 ± 2.9 kg CO2 /ha for UAV-based spraying. This corresponds to a mean reduction of 48.3% in total carbon emissions, primarily driven by the elimination of diesel fuel and the reduced use of pesticides under UAV practices. As shown in Table 6, diesel emissions were the dominant contributor to carbon load under conventional methods, while UAV spraying relied on electricity and incurred significantly lower pesticide-related emissions.

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Table 6. Carbon footprint comparison (conventional vs. UAV spraying). Method

Fuel Emissions (kg CO2)

Electric Emissions (kg CO2 /ha)

Chemical Emissions (kg CO2 /ha)

Total CO2 (kg/ha)

Conventional UAV

31–36 ~0

~0 15–20

13–16 7–9

45–52 22–31

A one-tailed t-test confirmed the statistical significance of this difference (p < 0.001), validating the carbon benefits of UAV spraying. The reduction was particularly notable in Punjab and Haryana, where diesel-intensive practices dominate. 3.2.2. Water Footprint Estimation Results Using Equation (5), the total freshwater usage per hectare was evaluated for each spraying method. UAV spraying resulted in an average usage of 2430 ± 410 m3 /ha, significantly lower than the 7580 ± 1320 m3 /ha associated with conventional operations. This translates into a 67.9% reduction in operational water footprint. The impact of these reductions on regional groundwater overdraft is outlined in Table 7, which highlights the estimated savings per hectare in Punjab, Haryana, and Rajasthan. For instance, in Punjab, the use of UAVs could reduce groundwater overdraft by approximately 5300 m3 /ha, equating to a 53% relief. Table 7. Potential GW overdraft relief from UAV adoption by region.

Region

GW Overdraft (m3 /ha/yr)

Conv Spray (m3 /ha)

UAV (m3 /ha)

Saving (m3 /ha)

% Overdraft Relief

Punjab Haryana Rajasthan

10,000 9000 7000

7600 7400 7300

2300 2500 2400

5300 4900 4900

~53% ~55% ~70%

Given that agricultural irrigation is a major source of groundwater extraction in Northern India, the observed water savings from UAV spraying have significant implications for aquifer health. Using Central Ground Water Board (CGWB) overdraft estimates, the perhectare water savings of ~5150 m3 from UAV spraying were mapped against the regional overdraft levels. For areas relying heavily on tubewell irrigation, that saving equates to the following: GW Stress Reduction =

5150 m3 saved ≈ 50–70% annual depletion

These figures from Table 7 illustrate that UAV spraying has the potential to alleviate 50–70% of annual aquifer overdraft in the studied regions. Such conservation gains are vital in the face of declining groundwater tables and mounting climate pressure on irrigation systems. This result supports the adoption of UAV spraying as a strategic intervention for aquifer conservation in overexploited districts. 3.2.3. Pesticide Runoff Estimation Results The pesticide runoff potential, modeled using Equation (6), showed a significant reduction under UAV usage. The mean pesticide runoff was estimated at 0.62 ± 0.08 kg/ha for UAVs, compared to 1.95 ± 0.2 kg/ha for conventional methods—a reduction of ~68%. This was largely attributed to reduced application rates and precision targeting via UAVs. The final estimates are summarized in Table 8.

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Table 8. Pesticide runoff potential.

Method

Pesticide Use (kg/ha)

Runoff Coefficient (RC)

Estimated Runoff (kg/ha)

Conventional UAV

3.12 1.84

0.25 0.20

0.78 0.37

These reductions are consistent with prior studies on UAV-mediated drift control and chemical precision. 3.2.4. Monte Carlo Simulation: Uncertainty Analysis Results To account for variability in environmental conditions and parameter uncertainty, we conducted a Monte Carlo simulation with 10,000 iterations for each key environmental metric: CO2 emissions, water usage, and pesticide runoff. The simulation assumed a normal distribution for each variable, using empirically derived means and standard deviations based on the raw data collected from UAV and conventional farm trials. The 95% confidence intervals derived from the simulation outputs for each category are summarized in Table 9. Table 9. Monte Carlo simulation—95% confidence intervals.

Impact Category

Conventional (95% CI)

UAV (95% CI)

% Reduction

CO2 Emissions (kg CO2 /ha) Water Usage (m3 /ha) Pesticide Runoff (kg/ha)

28.48–38.34 5017.3–10,119.8 1.55–2.34

2.65–6.96 1621.9–3235.8 0.46–0.78

~85% ~67–70% ~68%

Figure 3 presents the resulting probability density histograms for each environmental impact category, comparing the conventional and UAV spraying methods. Each curve represents the likelihood distribution of total impact per hectare. Histogram peaks (Figure 3) show non-overlapping 95% CIs, confirming robust environmental advantages.

Figure 3. Monte Carlo simulation histograms for environmental impact metrics. Probability distributions for CO2 emissions (left), water usage (center), and pesticide runoff (right) across UAV and conventional spraying methods. UAV distributions are visibly narrower and shifted left, indicating both reduced mean impact and lower variability.

This quantitative uncertainty modeling strengthens the credibility of the LCA outcomes by incorporating stochastic risk evaluation, as recommended by the current best practices in agricultural sustainability assessments. 3.2.5. Tornado Sensitivity Analysis Results The Tornado Sensitivity Analysis quantifies the relative influence of key operational variables on UAV spraying's environmental performance, specifically total carbon emissions and water usage per hectare. The analysis identified diesel use, spray volume, and

pesticide dosage as the most impactful variables. These findings are presented visually in Figure 4, which shows the Tornado Chart for UAV spraying environmental sensitivity. To complement this chart, Table 10 presents the sensitivity rankings along with each variable's baseline output and the resulting impact% on environmental performance. The "Impact (%)" was computed using Equation (8), based on the difference between the maximum and minimum output values divided by the baseline.

Figure 4. Tornado Sensitivity Analysis for UAV spraying (n = 18). Bars show percentage change in environmental efficiency (%) when each input is varied ±20% around its baseline value. Table 10. Tornado Sensitivity Results with Baseline Outputs and Impact %.

Input Variable

Baseline Output (kg CO2 /ha or m3 /ha)

Impact on Environmental Performance (%)

Diesel Use (Ediesel) Spray Volume (SV) Pesticide Volume (Puse) Spraying Efficiency (Drift, Coverage) Meteorological Conditions Battery Efficiency (Eelectric)

30.0 kg CO2 /ha 2430 m3 /ha 1.84 kg/ha Qualitative drift proxy 2430 m3 /ha (linked to spray loss) 25.0 kWh/ha (converted to CO2)

15% 12% 9% 7% 5% 4%

The analysis confirms that diesel substitution and low-volume spraying are key levers for reducing UAV spraying's environmental footprint. In contrast, battery efficiency and meteorological variability showed lesser sensitivity, suggesting operational robustness under changing field conditions. This ranking can inform both device design optimization (e.g., nozzle selection, automated volume control) and regulatory priorities (e.g., energy efficiency incentives, precision dosing mandates). Furthermore, these sensitivity results support the development of intelligent UAV spraying protocols, such as those proposed in our IMM framework, that could adapt spraying behavior based on these parameters in real time. In addition to the one-at-a-time (OAT) ranking, we tested first-order interactions among the three most influential inputs (diesel use, spray volume, pesticide volume) using a fractional factorial ±20% design (23 runs). Table 11 shows that every two-factor interaction contributed ≤ 6% of total variance—well below the main-effect contributions of 15% (diesel), 12% (spray volume), and 9% (pesticide volume). This confirms that interaction terms are comparatively weak within the studied operating ranges, validating the OAT approach for sensitivity ranking purposes.

Table 11. Pair-wise interaction effects (±20% perturbation).

Interaction Term

Δ CO2 (kg ha−1)

% Total Variance

Δ Water (m3 ha−1)

% Total Variance

Diesel × Spray Volume

+1.6

5%

+42

4%

Diesel × Pesticide Volume

+1.2

4%

+28

3%

Spray Volume × Pesticide Volume

+0.8

3%

+25

2%

Note: main-effect contributions were 15% (diesel), 12% (spray volume), and 9% (pesticide volume); see Figure 4.

3.2.6. Fuel and Electricity Cost Sensitivity Analysis Results This section evaluates the impact of energy price fluctuations on the cost dynamics of UAV-based and conventional pesticide spraying methods. Deterministic modeling was used to simulate energy cost variations using real-world ranges reported for diesel and electricity prices in India over the 2021–2024 period. Specifically, diesel prices were simulated in the range of INR 72–INR 108 L−1 (0.88–1.32 USD L−1) (±20% of base price INR 90 L−1 (1.10 USD L−1)), and electricity prices were simulated in the range of INR 5.6–INR 8.4 kWh−1 (0.068–0.102 USD kWh−1) (±20% of base price INR 7 kWh−1 (0.085 USD kWh−1)). The energy consumption baselines were taken from the raw data (Section 2.1.4), where conventional tractor sprayers consumed approximately 44.2 kWh equivalent energy per hectare (converted from diesel), while UAV operations consumed approximately 20.2 kWh per hectare via electric battery systems. The modeled cost sensitivity is summarized in Table 12, which captures the change in per-hectare energy cost under low-, baseline-, and high-price scenarios. All values are expressed in INR per hectare. Table 12. Energy cost sensitivity under variable price scenarios.

Method

Energy Type

Energy Use (kWh eq/ha)

Price Range (INR/unit; USD/unit †)

Low Cost (INR/ha; USD/ha †)

Base Cost (INR/ha; USD/ha †)

High Cost (INR/ha; USD/ha †)

Conventional

Diesel

44.2 kWh eq/ha (≈16.5 L)

INR 72–INR 108 L−1 (0.88–1.32 USD L−1)

1188 (14.5)

1485 (18.1)

1782 (21.7)

UAV Spraying

Electricity

20.2 kWh/ha

INR 5.6–INR 8.4 kWh−1 (0.068–0.102 USD kWh−1)

113 (1.38)

141 (1.72)

170 (2.07)

† Exchange rate as in Table 1.

The results clearly demonstrate that conventional spraying costs are far more sensitive to fuel price fluctuations. At the upper bound of diesel prices of INR 108 L−1 (1.32 USD L−1), energy costs per hectare rise to INR 1782 (21.7 USD), an increase of over 20% from the baseline. In contrast, UAV spraying, despite its reliance on electricity, remains relatively cost-stable, with per-hectare costs fluctuating only by ±INR 20–INR 25 (≈0.25–0.30 USD). This contrast in volatility underscores a key economic advantage of UAV adoption, especially in regions subject to unpredictable diesel pricing or supply chain disruptions. Moreover, this analysis reaffirms the results from Section 3.4 (Cost–Benefit Analysis) and provides further support for policy efforts aimed at subsidizing electricity use or establishing solar-powered UAV charging hubs to further stabilize operational costs in rural India. The results also support findings from techno-economic studies on sustainable AgriTech, where long-term viability is strongly tied to energy input predictability and operating expenditure (OPEX) control.

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3.3. Operational Efficiency Benchmarking (DEA Results) To evaluate the resource efficiency of UAV spraying systems relative to conventional methods, a Data Envelopment Analysis (DEA) framework was applied using the inputoriented CCR model. This model assessed how each farm (DMU) transformed agricultural inputs—namely water usage, pesticide volume, and energy consumption—into outputs such as crop yield and environmental performance improvements. DEA scores range from 0 to 1, where a score of 1.0 denotes full efficiency relative to the best-performing units on the frontier. We implemented DEA (Data Envelopment Analysis) manually using linear programming (LP) with scipy.optimize (SciPy Community, Austin, TX, USA) to compute efficiency scores for UAV and conventional farms and the summary score. To ensure transparency and allow the replication of efficiency results, Table 13 presents the raw input–output values and computed DEA efficiency scores for each of the 18 farms analyzed in this study. Farms 1–9 are conventional sprayer-operated fields, while Farms 10–18 are UAV-sprayed. The score distribution aligns with the visualizations: UAV farms consistently achieve DEA scores between 0.78 and 1.0, while conventional farms remain below 0.51, validating the robustness of DEA modeling. Table 13. DEA input–output dataset for 18 farms (9 conventional + 9 UAV) and their corresponding efficiency scores. Farm_ID

Method

Water (m3 per ha)

Pesticide (kg per ha)

Energy (kWh per ha)

Crop Yield (kg per ha)

DEA Score

Farm_1 Farm_2 Farm_3 Farm_4 Farm_5 Farm_6 Farm_7 Farm_8 Farm_9 Farm_10 Farm_11 Farm_12 Farm_13 Farm_14 Farm_15 Farm_16 Farm_17 Farm_18

Conventional Conventional Conventional Conventional Conventional Conventional Conventional Conventional Conventional UAV UAV UAV UAV UAV UAV UAV UAV UAV

7800 7200 7600 8100 7400 9000 8500 7000 6800 2500 2700 2300 2600 2100 2900 2400 3100 2200

3.2 3 3.1 3.3 2.9 3.5 3.4 2.8 3 1.9 1.7 1.6 1.8 1.5 2 1.8 2.1 1.6

45 43 42 47 40 50 48 39 41 22 20 18 21 17 24 19 23 18

5300 5200 5100 5400 5000 5500 5300 4900 5050 5300 5250 5150 5400 5200 5450 5350 5500 5200

0.48 0.5 0.47 0.47 0.50 0.45 0.45 0.50 0.49 0.86 0.90 0.93 0.87 1 0.79 0.92 0.78 0.95

This dataset underpins the entire DEA efficiency modeling. Notably, Farm_14, which achieved a perfect DEA score of 1.0, exemplifies the benchmark unit with the lowest input intensities and a high crop yield. This confirms that UAV farms not only reduce environmental burden but also optimize operational productivity, as established by multidimensional efficiency modeling. The distribution of DEA efficiency scores across the 18 farms (9 UAV and 9 conventional) revealed significant differences between the two groups. As shown in Figure 5, the DEA frontier plot visualizes each farm's performance in terms of water use (x-axis) and crop yield (y-axis), with the color scale denoting the DEA score. UAV farms clustered near the top-left quadrant—indicating higher yield per unit of water—were consistently more efficient. The red star marks the most efficient DMU, achieving the maximum output with the least water input, and representing a UAV-operated farm.

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Figure 5. DEA efficiency frontier for 18 farms. X-axis = water use (m3 ha−1). Y-axis = yield (kg ha−1). Point color represents DEA score (θ); red star = highest efficiency (θ = 1).

To further understand how input usage affects the DEA performance, scatter plots were constructed for each input metric against the DEA score as shown in Figure 6. Each subplot highlights a clear negative relationship between input use and efficiency. In the first subplot, water use is inversely related to the DEA score—farms consuming more water exhibit lower scores. The second and third subplots display similar trends for pesticide use and energy use, respectively. These visualizations confirm that UAV-operated farms, which consume fewer inputs per hectare, achieve higher efficiency outcomes. UAV farms show tighter clustering in the high-efficiency range. All three inputs exhibited a significant negative linear relationship with efficiency score—water ($R2 = 0.96$, 95% CI for slope [$-8.66 \times 10-5$, $-6.99 \times 10-5$]), pesticide ($R2 = 0.97$, 95% CI [−0.321, −0.265]), and energy ($R2 = 0.97$, 95% CI [−0.0187, −0.0153])—with $p < 0.01$ in each case, confirming that lower input use is strongly associated with higher relative efficiency.

(a)

(b)

(c)

Figure 6. (a–c) Relationship between individual inputs (n = 18) and DEA efficiency. (a) Water (m3 ha−1); (b) pesticide (kg ai ha−1); (c) energy (kWh ha−1). Scatter plots of (a) water use vs. DEA efficiency score ($R2 = 0.58$), (b) pesticide use vs. DEA efficiency score ($R2 = 0.54$), and (c) energy use vs. DEA efficiency score ($R2 = 0.62$). Each panel includes a fitted linear regression line illustrating the strength of the inverse relationship ($p < 0.01$).

The boxplot analysis of DEA scores, as shown in Figure 7, quantitatively emphasizes the performance difference. UAV farms exhibit a median DEA score of 0.89 with an interquartile range (IQR) of 0.85–0.95, while conventional farms demonstrate a significantly

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lower median score of 0.48 with an IQR of 0.45–0.50. The UAV group showed no outliers, whereas conventional farms had several observations falling below the 25th percentile, suggesting performance variability and inefficiency in resource usage.

Figure 7. Distribution of DEA scores (θ) by spraying method. Boxplot conventions as in Figure 1; UAV, n = 9; conventional, n = 9.

The frequency distribution of DEA scores as shown in Figure 8 further corroborates these findings. UAV farms cluster in the 0.85–1.0 efficiency range, while conventional farms predominantly fall between 0.45 and 0.55. No overlap exists in efficiency scores between the two groups, indicating a statistically and operationally significant separation in spraying performance.

Figure 8. Frequency of DEA efficiency scores (bin = 0.05) for UAV (yellow, n = 9) and conventional farms (blue, n = 9).

To assess the robustness of our DEA results for input selection, we recalculated efficiency scores in four scenarios: using all inputs (base), and excluding water, pesticide, or energy individually. Prior to DEA computation, all inputs and outputs were normalized to the [0–1] range via min–max scaling to remove scale bias. We also tested the effect of omitting the single lowest-efficiency DMU; group mean efficiencies changed by <0.01, indicating negligible outlier influence. As shown in Table 14, UAV-sprayed farms consistently maintain high mean efficiencies (≥0.88) across all scenarios, whereas conventional farms remain at ~0.48, demonstrating that the relative efficiency advantage of UAV spraying is not driven by any single input variable.

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Table 14. Sensitivity of DEA mean efficiency scores to input exclusion.

Scenario

Conventional Mean Efficiency

UAV Mean Efficiency

None (Base) Excluding Water Excluding Pesticide Excluding Energy

0.48 0.48 0.39 0.48

0.89 0.88 0.88 0.88

Efficiency scores were recalculated (input-oriented CCR DEA) under four scenarios: base (water, pesticide, energy), and excluding each input in turn. Means shown over n = 9 farms per group.

3.4. Intelligent Management Models (IMMs) for UAV Spraying Parameter Optimization The Intelligent Management Model (IMM) simulations, along with field-derived spraying trials, provided a clear evaluation of how different UAV configurations influenced spray coverage and drift behavior. A total of five trial scenarios were designed using varying combinations of droplet size, spray volume, nozzle type, and flight speed. Each configuration was implemented in field-like conditions representative of drone spraying service operations in North Indian agricultural belts. These simulations were calibrated using operational field data obtained from drone spraying service providers (DSPs) in Punjab, Haryana, and Rajasthan, between 2022 and 2023. Five UAV spraying trials were designed, covering a wide range of droplet sizes (150–250 µm), spray volumes (50–90 L/ha), and nozzle configurations (flat-fan, hollowcone, variable-rate). The results of each IMM trial, in terms of canopy coverage and drift percentage, are summarized in Table 15. Across all trials, the variable-rate nozzle configurations consistently outperformed flat-fan and hollow-cone setups. The highest spray coverage was recorded in Trial T3, where a variable-rate nozzle operating at a droplet size of 220 µm and a spray volume of 50 L per hectare achieved 95% canopy coverage, with only 8% drift loss. This trial used a moderate flight speed of 3 m per second, which proved optimal for balancing uniform deposition with UAV battery endurance. Table 15. IMM trial results: UAV spraying parameter optimization.

Trial ID

Nozzle Type

Droplet Size (µm)

Spray Volume (L/ha)

Flight Speed (m/s)

Coverage * (%)

Drift (%)

T1 T2 T3 T4 T5

Flat-Fan Hollow-Cone Variable-Rate Variable-Rate Flat-Fan

200 150 220 250 180

60 80 50 70 90

3.5 2.0 3.0 2.5 4.0

86 90 95 92 85

15 12 8 10 17

- Coverage percentages reported in Table 15 correspond directly to SCE values as defined in Equation (13).

To provide a more rigorous quantitative basis to the IMM outputs, we conducted Multiple Regression Analysis using trial data capturing spray coverage (%) and spray drift (%) as dependent variables. Coverage was modeled as a function of droplet size and spray volume, while drift was modeled against droplet size and flight height. The fitted models yielded R2 values of 0.81 for coverage and 0.72 for drift, with both models statistically significant ($p < 0.05$). Table 16 summarizes the regression coefficients and fit statistics. These results support the observed trends from the IMM optimization and strengthen the interpretability of Figure 9.

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Table 16. Fitted regression models for spray coverage and drift.

Dependent Variable

Predictor

Coefficient (β)

SE

p-Value

Spray Coverage (%)

Intercept

25.4

3.1

<0.001

Droplet Size (μm)

+0.32

0.05

<0.001

Spray Volume (L/ha)

+0.15

0.02

<0.001

Intercept

8.2

2.2

<0.001

Droplet Size (μm)

−0.28

0.04

<0.001

Flight Height (m)

+0.12

0.03

0.002

Spray Drift (%)

(a)

R2 0.81

0.72

(b)

Figure 9. Response surfaces fitted to 10 IMM field trials. (a) Spray coverage (%) versus Dropletdroplet size (μm) and Sprayspray volume (L ha−1). (b) Drift potential (%) versus Dropletdroplet size (μm) and Flightflight height (m). Mesh grid = 15 × 15 point show the fitted regression surfaces for spray coverage (Coverage = 25.4 + 0.32·DropletSize + 0.15·SprayVolume; R2 = 0.81) and spray drift (Drift = 8.2–0.28·DropletSize + 0.12·FlightHeight; R2 = 0.72), respectively. Surfaces are plotted from the regression coefficients in Table 16.

Regression surfaces (Figure 9) corroborate Table 16: variable-rate nozzles at 220–250 μm and 50–70 L ha−1 deliver ≥ 95% coverage with ≤10% drift. Trials situated in the lower quadrant of the drift axis (DPI < 10) aligned with the ideal coverage-to-drift ratios predicted by the IMM simulation. The model's predictive accuracy validated its potential to assist UAV operators in adjusting parameters proactively based on crop type, environmental conditions, and spray objectives. Overall, the IMM framework demonstrated that a variable-rate nozzle operating in the 220–250 μm droplet range, combined with a spray volume of 50–70 L/ha and a flight speed of 2.5–3.0 m/s, offers the most efficient and environmentally responsible configuration for UAV-based spraying in Indian agriculture. These findings validate the IMM's ability to proactively recommend UAV settings that maximize pesticide deposition while minimizing environmental risks. The integration of field-tuned parameters into this decision-support model offers real-time adaptability, making it suitable for use as a smart spraying assistant module in UAV firmware or operator dashboards. Ultimately, IMM-based optimization highlights the operational feasibility and agronomic advantages of adaptive nozzle technologies in Indian UAV spraying. When used under optimal conditions, these configurations can significantly reduce pesticide waste and off-target drift—reinforcing UAVs as a sustainable precision agriculture tool in India.

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3.5. Multi-Criteria Decision Analysis (MCDA) To evaluate the most impactful policy pathways for enhancing the adoption of UAV spraying technologies in Indian agriculture, a Multi-Criteria Decision Analysis (MCDA) was conducted. This framework incorporated four criteria reflecting both stakeholder priorities and documented drivers of precision agriculture adoption: economic feasibility, adoption feasibility, environmental impact, and government support readiness. The weight assigned to each criterion, based on stakeholder consultations and policy literature, is as follows: economic feasibility (0.30), adoption feasibility (0.25), environmental impact (0.25), and government support (0.20). These weights were also reflected in the scoring framework applied to each policy. Each policy was scored across these dimensions based on weighted importance values and stakeholder-informed utility estimates. Three leading policy interventions were evaluated within this framework. The first included government subsidy programs currently operational under the Sub-Mission on Agricultural Mechanization (SMAM) and NABARD-backed financial support structures. The second involved the Drone Didi Scheme, a women-centric training and employment program that aims to improve operator availability and community ownership of drone technologies. The third policy intervention pertained to the

regulatory fast-tracking of Drone Service Providers (DSPs) under India's Drone Rules (2021), which facilitate licensing and service delivery authorizations. As presented in Table 17, the highest total policy score was recorded for the government subsidy option, with a composite effectiveness score of 8.55. This is attributed to strong alignment across economic and environmental criteria. The Drone Didi Scheme followed closely with a score of 8.20, demonstrating high performance in social feasibility and institutional support. The Regulatory Fast-Tracking policy option, although beneficial for easing entry for private service providers, yielded a lower score of 7.25, primarily due to limited direct economic incentives for farmers and weaker environmental co-benefits. Table 17. MCDA-based policy effectiveness scores for UAV adoption interventions. Policy Option

Economic Feasibility (0.30)

Adoption Feasibility (0.25)

Environmental Impact (0.25)

Govt. Support Readiness (0.20)

Final Score

Government Subsidy (SMAM/NABARD)

2.70 (9 × 0.30)

2.00 (8 × 0.25)

2.25 (9 × 0.25)

1.60 (8 × 0.20)

8.55

Drone Didi Scheme (PIB, 2023)

2.40 (8 × 0.30)

2.25 (9 × 0.25)

1.75 (7 × 0.25)

1.80 (9 × 0.20)

8.20

Regulatory Fast-Tracking for DSPs

2.10 (7 × 0.30)

1.75 (7 × 0.25)

2.00 (8 × 0.25)

1.40 (7 × 0.20)

7.25

The radar plot (Figure 10) mirrors Table 17: subsidies dominate, Drone Didi is next, and regulatory fast-tracking ranks third. This visual confirms the numerical findings and emphasizes that a hybrid policy strategy —combining direct financial support with community-level capacity building and training programs—is likely to yield the most sustained and equitable adoption of UAV spraying technologies in Indian agriculture. The results clearly indicate that economic interventions, particularly capital cost subsidies, have the highest influence on technology adoption, especially among small and marginal farmers. Moreover, the incorporation of gender-responsive models, such as Drone Didi, has emerged as a promising complementary approach, not only addressing labor gaps but also enhancing inclusivity and local ownership. While streamlining of regulatory procedures remains important, its isolated impact may be limited without

simultaneous fiscal and capacity-building measures. These findings provide empirical support for integrated policy frameworks that combine financial, institutional, and social levers for sustainable UAV deployment in agriculture.

Figure 10. Weighted MCDA scores (0–10 scale) for three policy options: government subsidy, Drone Didi training, and regulatory fast-tracking. Axes correspond to criteria: economic, adoption, environmental, and institutional. Filled area denotes composite performance; larger radius indicates stronger performance.

- Conclusions and Discussion This study presented a comprehensive evaluation of UAV-based spraying systems in Indian agriculture by integrating multiple empirical and computational methodologies. The evidence across all analytical layers consistently highlights that UAV spraying offers considerable operational and environmental advantages over conventional tractor-mounted or manual pesticide application systems. In terms of resource efficiency, UAV operations demonstrated a 67.9% reduction in water use, 41.0% reduction in pesticide application, and 54.3% reduction in energy consumption relative to conventional practices. These differences were statistically significant, as confirmed by t-tests and regression analyses, and are particularly relevant for waterstressed agricultural belts such as Punjab, Haryana, and Rajasthan. The corresponding impact on groundwater conservation was substantial, with UAV-based methods potentially alleviating 50–70% of the annual aquifer overdraft per hectare. From an environmental standpoint, the Life Cycle Assessment (LCA) established that UAV spraying significantly reduces the total carbon footprint. This was supported by Monte Carlo simulations, which revealed 95% confidence intervals consistently favoring UAV systems across CO2 emissions, water footprint, and pesticide runoff potential. The Tornado Sensitivity Analysis further identified diesel usage, spray volume, and pesticide load as the most influential environmental levers, suggesting that optimization in these areas can further enhance sustainability outcomes. Efficiency benchmarking using Data Envelopment Analysis (DEA) revealed that UAVoperated farms consistently outperformed conventional ones, achieving higher technical efficiency scores even under similar yield conditions. This indicates that UAVs not only reduce input waste but also maintain or improve agronomic output. Moreover, the In-

telligent Management Model (IMM) validated that nozzle configurations, droplet size, and spray volume could be precisely calibrated to minimize off-target drift and maximize canopy coverage. Trials using variable-rate nozzles achieved 95% coverage with <10% drift, demonstrating the precision capabilities of modern UAV systems. In terms of policy interventions, the Multi-Criteria Decision Analysis (MCDA) revealed that financial subsidy schemes and the Drone Didi program were most effective in supporting scalable adoption. Subsidies emerged as the strongest enabler due to their role in offsetting capital cost burdens, while the Drone Didi initiative offered genderresponsive employment and decentralized service delivery. The radar chart comparison further reinforced the complementarity of these approaches, suggesting that integrated policy strategies hold the greatest potential for long-term UAV deployment. Taken together, the results affirm that UAV spraying, when deployed through optimized parameters and supported by enabling policies, represents a scalable and sustainable solution for addressing India's agricultural input challenges. The convergence of environmental efficiency, operational optimization, and socio-economic feasibility positions UAV technology as a critical lever for climate-smart agriculture in India. While this integrated analysis leverages multiple quantitative frameworks, several limitations warrant consideration. First, the sample size of 18 decision-making units may not capture the full heterogeneity of Indian agro-climatic and operational contexts. We are currently coordinating with additional Drone Service Providers and state extension agencies to scale the dataset to over 100 farms across five states and three cropping seasons, which will enable a more robust statistical validation of the findings. Second, field conditions such as wind speed, humidity, and canopy structure were not systematically controlled, introducing variability into spray efficiency measures. Third, the LCA boundary was limited to the use phase, omitting upstream (manufacturing) and downstream (decommissioning) impacts, which constrains the full cradle-to-grave assessment. Fourth, our sensitivity analysis used a one-at-a-time (OAT) approach and did not model interactions; future work should adopt global sensitivity methods (e.g., Sobol indices or factorial designs) to capture parameter interdependencies. Finally, the cross-sectional design prevents the evaluation of temporal dynamics. Future research should address these gaps by expanding the DMU dataset, incorporating real-time environmental sensing for adaptive IMM calibration, extending the LCA to a full life cycle scope, and conducting longitudinal multi-season trials to validate and generalize the findings across diverse cropping systems. Overall, despite the limitations, this work demonstrates the promise of UAV spraying for climate-smart agriculture in India and provides a robust, data-

driven foundation for future operational and policy development. Author Contributions: Conceptualization, S.V.R.; Methodology, S.V.R.; Software, S.V.R.; Validation, S.V.R.; Data curation, S.V.R.; Writing—original draft, S.V.R.; Writing—review & editing, P.K.V. and V.T.; Visualization, P.K.V.; Supervision, P.K.V. and V.T. All authors have read and agreed to the published version of the manuscript. Funding: This research received no external funding. Institutional Review Board Statement: Not applicable. Informed Consent Statement: Not applicable. Data Availability Statement: All datasets and analysis scripts (including Python code for figures and regression modeling) are available at https://github.com/rss2019003/Sustainability, accessed on 30 June 2025. Conflicts of Interest: The authors declare no conflict of interest.

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Review

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Drones: Innovative Technology for Use in Precision Pest Management Fernando H. Iost Filho,1, Wieke B. Heldens,2 Zhaodan Kong,3 and Elvira S. de Lange4, Department of Entomology and Acarology, University of São Paulo, Piracicaba, São Paulo, Brazil, 2German Aerospace Center (DLR), Earth Observation Center, German

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Abstract Arthropod pest outbreaks are unpredictable and not uniformly distributed within fields. Early outbreak detection and treatment application are inherent to effective pest management, allowing management decisions to be implemented before pests are well-established and crop losses accrue. Pest monitoring is time-consuming and may be hampered by lack of reliable or cost-effective sampling techniques. Thus, we argue that an important research challenge associated with enhanced sustainability of pest management in modern agriculture is developing and promoting improved crop monitoring procedures. Biotic stress, such as herbivory by arthropod pests, elicits physiological defense responses in plants, leading to changes in leaf reflectance. Advanced imaging technologies can detect such changes, and can, therefore, be used as noninvasive crop monitoring methods. Furthermore, novel methods of treatment precision application are required. Both sensing and actuation technologies can be mounted on equipment moving through fields (e.g., irrigation equipment), on (un)manned driving vehicles, and on small drones. In this review, we focus specifically on use of small unmanned aerial robots, or small drones, in agricultural systems. Acquired and processed canopy reflectance data obtained with sensing drones could potentially be transmitted as a digital map to guide a second type of drone, actuation drones, to deliver solutions to the identified pest hotspots, such as precision releases of natural enemies and/or precision-sprays of pesticides. We emphasize how sustainable pest management in 21st-century agriculture will depend heavily on novel technologies, and how this trend will lead to a growing need for multi-disciplinary research collaborations between agronomists, ecologists, software programmers, and engineers. Key words: biological control, integrated pest management, precision agriculture, remote sensing, unmanned aerial system

Arthropod pest outbreaks in field crops and orchards often show nonuniform spatial distributions. For some pests, such as cabbage aphids [Brevicoryne brassicae L. (Hemiptera: Aphididae)] in canola fields (Brassica spp.), and Asian citrus psyllids [Diaphorina citri Kuwayama (Hemiptera: Liviidae)] in citrus orchards (Citrus spp.) there is evidence of highest population densities along field edges (Sétamou and Bartels 2015, Severtson et al. 2015, Nguyen and Nansen 2018). For other pests, such as soybean aphids [Aphis glycines Matsumura (Hemiptera: Aphididae)] in soybean (Glycine max (L.) Merrill), and two-spotted spider mites [Tetranychus urticae Koch (Acari: Tetranychidae)] in cowpea (Vigna unguiculata (L.) Walp.), parts of fields that are exposed to abiotic stress, such as drought or nutrient deficiencies, tend to be more susceptible (Mattson and Haack 1987, Abdel-Galil et al. 2007, Walter and

DiFonzo 2007, Amtmann et al. 2008, West and Nansen 2014). Thus, as pests are spatially aggregated, precision agriculture technologies can offer important opportunities for integrated pest management (IPM) (Lillesand et al. 2007). Precision pest management is twofold: first, reflectance-based crop monitoring (using ground-based, airborne, or orbital remote sensing technologies) can be used to identify pest hotspots. Second, precision control systems, such as distributors of natural enemies and pesticide spray rigs, can provide localized solutions. Both technologies can be mounted on equipment moving through fields (such as irrigation equipment), on manned or unmanned vehicles driving around in fields, or on aerial drones. In this review, we focus specifically on the use of small drones in IPM. Small drones are here defined as remotely controlled,

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although there is a big margin among predictions of future drone use, an increasing number of growers is expected to use and/or own a drone within the next decade. There are various ways to classify drones (Watts et al. 2012). For our purpose, we currently distinguish two major types of small drones: rotary wing and fixed wing. Each of these has its own advantages and limitations (Hogan et al. 2017). Multi-rotor and single-rotor (helicopter) drones do not require specific structures for take-off and landing. Moreover, they can hover and

perform agile maneuvering, making them suitable for applications (e.g., inspection of crops and orchards or pesticide applications) where precise maneuvering or the ability to maintain a visual of a target for an extended period of time is required. Especially multirotor drones tend to be easy to use, and relatively cheap to obtain. Fixed-wing systems are usually faster than rotor-based systems, and generally larger in size, allowing for higher payloads (Stark et al. 2013b, Dalamagkidis 2015). Both have been used for precision agriculture (Barbedo 2019). Since drone technology quickly improves, we will refrain from discussing drone types in further detail, but see Dalamagkidis (2015) and Stark et al. (2013b) for more information. A number of reviews discuss the use of drones in precision agriculture, focusing on airborne remote sensing for various applications, such as predicting yield and characterizing soil properties (Hardin and Jensen 2011, Prabhakar et al. 2012, Zhang and Kovacs 2012, Mulla 2013, Gago et al. 2015, Nansen and Elliott 2016, Pádua et al. 2017, Hunt and Daughtry 2018, Aasen et al. 2018, Gonzalez et al. 2018, Barbedo 2019, Maes and Steppe 2019). In this review, we focus on precision management of arthropod pests and describe the use of both sensing and actuation drones. First, we provide an update about airborne remote sensing-based detection of pest problems. Then, we evaluate the possibilities of actuation drones for precision distribution of pesticides and natural enemies. Also, we discuss the possibilities of sensing and actuation drones for

Fig. 1. (a) State-of-the-art open-loop remote sensing paradigm and (b) closed-loop IPM paradigm envisioned in this article. Sensing drones could be used for detection of pest hotspots, while actuation drones could be used for precision distribution of solutions. Adapted from Teske et al. (2019).

unmanned flying robots that weigh more than 250 g but less than 25 kg, including payload (FAA 2018a). These types of drones typically have flight-times of a few minutes to hours and limited ranges (Hardin and Jensen 2011). We will also briefly discuss the larger drones that are typically used for pesticide sprays. Discussion of smaller and larger drones is beyond the scope of this review, but see Watts et al. (2012), and Anderson and Gaston (2013) for more information. Drones used for detection of pest hotspots are here referred to as sensing drones, while drones used for precision distribution of solutions are referred to as actuation drones. Both types of drones could communicate to establish a closed-loop IPM solution (Fig. 1). Importantly, use of drones in precision pest management could be cost-effective and reduce harm to the environment. Sensing drones could reduce the time required to scout for pests, while actuation drones could reduce the area where pesticide applications are necessary, and reduce the costs of dispensing natural enemies. Reports of drones in agriculture started appearing around 1998 and increased dramatically in the last decade (Fig. 2). According to the abstract of a licensed report, the worldwide drone market value is currently estimated about $6.8 billion and is anticipated to reach $36.9 billion by 2022 (WinterGreen Research 2016b). Another paid report predicts that drones will reach a value of $14.3 billion by 2028 (Teal Group 2019). Agricultural small drones currently account for about $500 million, and their value is expected to reach $3.7 billion by 2022 (WinterGreen Research 2016a). A different paid report predicts similar values (ABI Research 2018), while a freely available resource predicts the value of drone-based solutions for agriculture at $32 billion (PwC 2016). Recently, the United Nations published a report on the use of drones for agriculture, stressing its potential benefits for food security (Sylvester 2018). A text message poll among ca. 900 growers based in the United States showed that around 30% use drone-based technology for farming practices (Farm Journal Pulse 2019). Thus,

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novel functions in pest management. Lastly, we discuss challenges and opportunities in the adoption of drone technology in modern agriculture.

Sensing Drones to Monitor Crop Health Traditional field scouting for pest infestations is often expensive and time-consuming (Hodgson et al. 2004, Severtson et al. 2016b, Dara 2019). It may be practically challenging, such as when a large acreage is involved, when the arthropod pests are too small to see with the naked eye, or when they reside in the soil or in tall trees. In some cropping systems, effective scouting is hampered by lack of reliable pest sampling techniques. Hence, one of the main drivers for the implementation of drone-based remote sensing technologies into agriculture is the potential time saved by automatizing crop monitoring, making the technology cost-effective for growers (Carrière et al. 2006, Backoulou et al. 2011a, Dara 2019). Compared to conventional platforms for remote sensing, such as ground-based, aerial (with manned aircraft) and orbital (with satellites such as Landsat [30 m spatial resolution], Sentinel 2 [10 m] or RapidEye [5 m]; Mulla 2013), sensing drones present several advantages that make them attractive for use in precision agriculture.

Sensing drones potentially allow for coverage of larger areas than ground-based, handheld devices. They can fly at lower altitudes than manned aircraft and orbital systems, increasing images' spatial resolution and reducing the number of mixed pixels (pixels representing reflectance of both plant and soil, discussed in more detail below). Also, they cost less to obtain and deploy than manned aircraft and satellites and do not have long revisiting times like satellites, allowing for higher monitoring frequencies (Zhang and Kovacs 2012, Mulla 2013, Matese et al. 2015, Aasen and Bolten 2018, Barbedo 2019, Maes and Steppe 2019).

Remote Sensing in Precision Agriculture Remote sensing is the detection of energy emitted or reflected by various objects, either in the form of acoustical energy or in the form of electromagnetic energy (including ultraviolet [UV] light, visible

light, and infrared light) (Usha and Singh 2013). It is a non-invasive, relatively labor-extensive method that could be used to detect plant stress before changes are visible by eye. For crops, remote sensing equipment generally assesses the spectral range of visible light or photosynthetically active radiation (PAR, 400–700 nm) and nearinfrared light (NIR, 700–1,400 nm), with most studies referring to the 400–1,000 nm range (Nansen 2016). Particular stressors, such as arthropod infestations, induce physiological plant responses, causing changes in the plants' ability to perform photosynthesis, which leads to changes in leaf reflectance in parts of this spectral range. For aerial remote sensing, a drone can be equipped with an RGB (red green blue) sensor, a multispectral sensor with between 3 and 12 broad spectral bands, or a hyperspectral sensor with hundreds of narrow spectral bands. An RGB sensor is low-cost, but results in limited spectral information. A multispectral sensor results in more spectral information, but a hyperspectral sensor is generally much better at differentiating subtle differences in canopy reflectance than a multispectral sensor (Yang et al. 2009a). However, since hyperspectral sensors are generally larger, they would require mounting on drones adapted for heavier payloads. Also, they are generally more expensive, and data analysis requires more time and experience, limiting use for individual growers. A comprehensive review of the sensor types compatible with drones has been written by Aasen et al. (2018).

Remote Sensing and Arthropod Pests Remote sensing technologies have been used in precision agriculture for the last few decades, with various applications, such as yield predictions and evaluation of crop phenology (Mulla 2013). Also, these techniques are being used to monitor different abiotic plant stressors, such as drought (Gago et al. 2015, Katsoulas et al. 2016, Zhao et al. 2017, Jorge et al. 2019) and nutritional deficiencies (Quemada et al. 2014), and biotic plant stressors, such as pathogens (Calderón et al. 2013, Mahlein et al. 2013, ZarcoTejada et al. 2018), nematodes (Nutter et al. 2002), and weeds (Rasmussen et al. 2013, Peña et al. 2015). Likewise, remote sensing technologies have been successfully used to detect stress caused by various arthropod pests on a wide variety of field and orchard crops (Riley 1989, Nansen 2016, Nansen and Elliott 2016; Tables 1–4). A limited amount of studies concerning arthropod-induced stress detection used drone-based aerial remote sensing (Table 1), manned aircraft-based aerial remote sensing (Table 2), or orbital remote sensing (Table 3), while most studies used ground-based remote sensing (Table 4). In these tables, optical sensors are grouped, in addition to the platform, they are mounted on, into RGB, multispectral, and hyperspectral sensors. As stated above, generally, multispectral sensors have 3–12 broad spectral bands at selected wavelength ranges, whereas hyperspectral sensors have many (usually >20, but up to several hundreds) narrow, contiguous spectral bands, acquiring the spectrum within the selected spectral region with many measurement points. However, there is no clear agreed on definition. Therefore, the tables include multispectral sensors acquiring more than 12 spectral bands. While grouping the sensors, we adhered to the authors' classifications (Tables 1–4). Tables 1–4 focus on detection of arthropod pests; we did not address diseases caused by arthropod vectors (e.g., Garcia-Ruiz et al. 2013). Also, these tables only contain studies related to crops and orchards. We did not address forestry studies, as the body of literature on pest detection involves multi-species forests, adding an additional layer of complexity as opposed to crops and orchards

Fig. 2. Number of articles published between 1998 and 2018 on the use of drones in agriculture. Shown is the number of publications for each year mentioning 'drone', 'UAV' (Unmanned Aerial Vehicle), or 'UAS' (Unmanned Aerial System) and 'agriculture'. The words 'bee', 'honey bee', and 'hive' were explicitly excluded from the search, to avoid including publications on drones defined as male bees. Source: Web of Science.

3

Type

Spectral resolutiona Sensor details
No. of specField tral bands observations
Plant common name
Mini-MCA6, Tetracam Inc.
M
M
M
Four rotors Matrice 100, SZ DJI Technology Co. Six rotors Spreading Wings S800, SZ DJI Technology Co.
eBee, senseFly
S110 NIRb, Canon 3
6
3
6
Arthropod counts
Damage assessments
Sorghum
Potato
Arthropod Canola counts, soil and plant tissue nutrient analysesc Damage as- Cotton sessments
b
a
Cotton jassid
Arthropod common name
Sorghum bicolor
Solanum tuberosum
Gossypium hirsutum L.
Brassica spp.
Thrips
Allium cepa L.
Sugarcane aphid
Colorado potato beetle
Two-spotted spider mite
Melanaphis sacchari Hemiptera: Aphididae
Coleoptera: Chrysomelidae Leptinotarsa decemlineata
Hunt and Rondon 2017, Hunt et al. 2017 Stanton et al. 2017
Acari: Tetranychidae Huang et al. 2018
Nebiker et al. 2016 Severtson et al. 2016a
Vanegas et al. 2018b
Vanegas et al. 2018a
Del-CampoSanchez et al. 2019 Zhang et al. 2014
References
Tetranychus urticae

Green peach aphid Myzus persicae

Thysanoptera: Thripidae Hemiptera: Aphididae

Hemiptera: Phylloxeridae

Grape phylloxera Daktulosphaira vitifoliae

Vitis vinifera

NA

Hemiptera: Phylloxeridae

Lepidoptera: Noctuidae

Hemiptera: Cicadellidae

Order: Family

Grape phylloxera Daktulosphaira vitifoliae Fitch

Jacobiasca lybica Bergevin and Zanon Spodoptera frugiperda Smith

Arthropod species

Vitis vinifera

Triticum aestivum Fall armyworm

Vitis vinifera L.

Plant species

RGB = red green blue, M = multispectral, H = hyperspectral. NIR = near infrared. c Remote sensing was used to detect nutrient deficiencies, which were correlated to arthropod presence. NA = information not provided.

Fixed wing

ADC-Lite, Tetracam Inc.

M

Eight rotors

Cinestar-8 MK Heavy Lift, Freefly Systems

Mini-MCA6, Tetracam Inc.

RGB

Four rotors

md4-1000, Microdrones

Grape 3 Visual inα ILCE-5100L with spection of an E 20 mm F2.8 images lens, Sony Wheat 3+3 Outbreak Aeryon Scout, Four rotors RGB + M Photo3S, Aeryon reported by Aeryon Labs Inc. Labs Inc. + ADCgrower Lite, Tetracam Inc. 3 + 5 + 274 Ground traps Grape S800 EVO, SZ DJI Six rotors RGB + M + H 5DsR, Canon Inc. and root Technology Co. + RedEdge, digging, MicaSense Inc. + visual vigor Nanoassessments Hyperspec, Headwall Photonics Inc. S800 EVO, SZ DJI Six rotors / RGB + M + 5DsR, Canon Inc. 3 + 5 + 274 Ground traps Grape H / RGB + RedEdge, four roTechnology Co. /3 and root MicaSense Inc. + tors / Phantom3 Pro, digging, NanoSZ DJI Techvisual vigor Hyperspec, nology Co. assessments Headwall Photonics Inc. / Phantom3 Pro associated camerab eBee, senseFly Fixed wing M S110 NIRb, Canon 3 NA Onion

Platform details

Table 1. Studies on drone-based hyperspectral, multispectral, and RGB remote sensing to detect arthropod-induced stress in crops and orchards

4 Journal of Economic Entomology, 2020, Vol. 113, No. 1

SSTCRIS, SST Development Group Inc. TerrAvion MS3100, DuncanTech

CASI, Borstad Associates + EO Camera, NASA ARCd SAMRSS + AVNIR, OptoKnowledge Systems SAMRSS + AVNIR, OptoKnowledge Systems AVIRIS, NASA

M

M

M

H

H

H

120– 240

50

224

4 + 60

4 + 60

4-8d

2 3

3

3

3

3

3 3

3

NA

3

NA

No. of spectral bands

Plant common name

Visual inspection of images Damage assessments

Arthropod counts

Arthropod counts

Arthropod counts

Root digging

Proportion of infested plants Arthropod counts Arthropod counts or visual inspection

Visual inspections

Damage assessments

Corn

Wheat

Cotton

Cotton

Cotton

Grape

Wheat Wheat

Wheat

Wheat

Sorghum

Visual inspections, sooty Citrus mold assessmentsb Arthropod counts, sooty Citrus mold assessmentsb Visual inspections, sooty Cotton mold assessmentsb Arthropod counts Cotton Sweep net sampling, drop Cotton cloth sampling Sweep net sampling Cotton

Arthropod counts, sooty Citrus mold assessmentsb

Field observations

Zea mays

Triticum aestivum

Gossypium hirsutum

Gossypium hirsutum

Gossypium hirsutum

Vitis vinifera

Triticum aestivum Triticum aestivum

Triticum aestivum

Triticum aestivum

Sorghum bicolor

Gossypium hirsutum

Gossypium hirsutum Gossypium hirsutum

Gossypium hirsutum

Citrus spp.

Citrus spp.

Citrus spp.

Plant species

b

M = multispectral, H = hyperspectral. A fungus not infesting the plant, but growing on the arthropod's sugary honeydew secretions. c Institute of Technology and Development. d Primary project sensors; five additional sensors were used with 3–8 spectral bands. NA = information not provided.

a

M+H

M+H

AISA, Specim Spectral Imaging Ltd. RDACS-H4, ITDc, Stennis Space Center

MS3100, DuncanTech

M

M M

RDACS, ITDc, Stennis Space Center MS3100, DuncanTech

M

M M

M

M

M

K-17, Fairchild Camera and Instrument Corp. + Hasselblad camera System composed of 3 video cameras K-17, Fairchild Camera and Instrument Corp. System composed of 3 video cameras MS2100, DuncanTech CRSP, NASA

Sensor details

Bemisia tabaci

Silverleaf whitefly

Strawberry spider mite Russian wheat aphid European corn borer

Spider mite

Cotton aphid

Grape phylloxera

Russian wheat aphid Hessian fly Greenbug

Russian wheat aphid

Sugarcane aphid

Ostrinia nubilalis

Tetranychus turkestani Ugarov and Nikolskii Diuraphis noxia

Tetranychus spp.

Aphis gossypii

Mirik et al. 2014 Carroll et al. 2008

Lepidoptera: Crambidae

Diptera: Cecidomyiidae Bhattarai et al. 2019 Hemiptera: Aphididae Elliott et al. 2009; Backoulou et al. 2015, 2016 Hemiptera: Lobits et al. 1997 Phylloxeridae Hemiptera: Aphididae Reisig and Godfrey 2006, 2010 Acari: Tetranychidae Reisig and Godfrey 2006 Acari: Tetranychidae Fitzgerald et al. 2004

Mayetiola destructor Say Schizaphis graminum

Hemiptera: Aphididae

Hemiptera: Aphididae Diuraphis noxia

Daktulosphaira vitifoliae

Hemiptera: Aphididae Diuraphis noxia

Elliott et al. 2015; Backoulou et al. 2018a, b Backoulou et al. 2011a,b, 2013, 2016 Elliott et al. 2007

Hemiptera: Aphididae

Melanaphis sacchari

Beet armyworm Spodoptera exigua Hübner Lepidoptera: Noctuidae Sudbrink et al. 2003 Tarnished plant Lygus lineolaris Palisot de Hemiptera: Miridae Willers et al. 1999 bug Beauvois Tarnished plant bug Lygus lineolaris Hemiptera: Miridae Willers et al. 2005

Hart and Meyers 1968 Hemiptera: Aleyrodidae Everitt et al. 1996

Hemiptera: Coccidae

Coccus hesperidum L.

Brown soft scale

Citrus blackfly

Hemiptera: Aleyrodidae Everitt et al. 1994

References

Aleurocanthus woglumi

Order: Family

Hemiptera: Aleyrodidae Hart et al. 1973

Arthropod species Aleurocanthus woglumi Ashby

Citrus blackfly

Arthropod common name

M

Spectral resolutiona

Table 2. Studies on aerial (manned aircraft) hyperspectral and multispectral remote sensing to detect arthropod-induced stress in crops and orchards

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6

Table 3. Studies on orbital multispectral remote sensing to detect arthropod-induced stress in crops

Spectral resolutiona Sensor details

No. of spectral Field bands observations

Plant common name Plant species

Arthropod Arthropod common name species

QuickBird, DigitalGlobe

3

Arthropod counts

Cotton

Gossypium hirsutum

Cotton aphid

M

QuickBird, DigitalGlobe

3

Arthropod counts

Cotton

Gossypium hirsutum

Spider mite

M

Terra, MODIS, NASA

36

Arthropod counts

Wheat

Triticum aestivum Wheat stem sawfly

M

Sentinel-2, S2AL1C, ESAb

13

Arthropod counts

Wheat

Triticum aestivum Hessian fly

M

HJ-1A/B, CCD sensor, NDRCC/ SEPAc,

4

Triticum aestivum Wheat aphid

M

Landsat-8, NASA

9

M

Landsat-5 TM, NASA

7

Wheat Arthropod counts, damage assessments Arthropod Wheat counts Arthropod Wheat counts

M

RapidEye, Planet Labs

5

Arthropod counts

Corn

Zea mays

Stem borer

M

HJ-1A/B, CCD sensor, NDRCC/ SEPAc,

4

Damage assess-Corn ments

Zea mays

Oriental Mythimna armywormd separata Walkerd

Triticum aestivum Wheat aphid Triticum aestivum Aphid

References

Aphis gossypii Hemiptera: Aphididae

Reisig and Godfrey 2006, 2010 Tetranychus Acari: Reisig and spp. Tetranychidae Godfrey 2006 Cephus cinctus Hymenoptera: Lestina Norton Cephidae et al. 2016 Mayetiola de- Diptera: Bhattarai structor Cecidomyiidae et al. 2019 Sitobion avenae Hemiptera: Luo et al. Aphididae 2014

Sitobion avenae Hemiptera: Aphididae NA Hemiptera: Aphididae Busseola spp.

Lepidoptera: Noctuidae

Lepidoptera: Noctuidae

Ma et al. 2019 Huang et al. 2011 AbdelRahman et al. 2017 Zhang et al. 2016

M = multispectral. European Space Agency. c National Committee for Disaster Reduction and State Environmental Protection Administration of China. d The arthropod species was originally misidentified as Spodoptera frugiperda; a correction was issued. NA = information not provided. a

b

in monoculture. More information about remote sensing in forestry settings can be found elsewhere (Dash et al. 2016, Pádua et al. 2017, Stone and Mohammed 2017, Dash et al. 2018). It is important to note that with remote sensing, not the pests themselves are detected, but patterns of canopy reflectance that are indicative of arthropod-induced plant stress. Field observations to confirm the presence of specific stressors remain necessary, but field scouting can be more efficiently focused with the a priori knowledge from remote sensing.

Analysis of Reflectance Spectra For the detection of plant stress using remote sensing, the spectral reflectance (the spectral signature or spectrum) of the vegetation is analyzed. Figure 3 shows a spectrum of healthy soybean leaves as recorded by a ground-based hyperspectral field spectrometer, together with the same

spectrum resampled to the spectral resolution of a hyperspectral imaging spectrometer for drones, and a multispectral sensor for drones. The figure shows the large loss of information between a hyperspectral sensor and a multispectral sensor. With higher spectral resolutions (i.e., more spectral bands), detailed spectral characteristics become visible and can be used to analyze vegetation spectra. This analysis can be done in various ways, e.g., by analyzing spectral reflectance features (e.g., absorption bands or reflectance peaks) that can be directly related to plant physiology, or indirectly

by building vegetation indices (VIs). These two techniques are addressed below exemplarily. An overview of techniques to quantify vegetation biophysical variables using imaging spectroscopy is given in Verrelst et al. (2019).

Spectral Features and VIs An important spectral feature light region is the red edge, i.e., the slope between the red and near infrared region of the spectrum, around 700 nm. This spectral region relates to the chlorophyll concentration (Horler et al. 1983, Delegido et al. 2011, Huang et al. 2015b) and the Leaf Area Index (LAI), the area of green leaves per unit of ground area (Delegido et al. 2013). The red edge position (REP), the point of maximum slope in the red edge region, is a valuable indicator of stress and senescence (Das et al. 2014, Verrelst et al. 2019), possibly because various stressors decrease leaf chlorophyll concentrations (Carter and Knapp 2001). For instance, an increased reflectance around 740 nm is associated with spider mite susceptibility in corn (Zea mays L.) (Nansen et al. 2013). Also, the overall reflection level of the spectrum might be characteristic. It should be noted that a spectrum of an imaging spectrometer, such as one mounted on drones, always describes an area, not a point. This area, or pixel size, depends on the flight height of the drone and can range from less than 1 cm2 to more than 10 cm2. With larger pixels, the recorded spectrum consists of reflectance of both

M

Order: Family

H

H H

H

H

H

H

M

M

M

FieldSpec FR spectroradiometer, ASD FieldSpec 4 Hi-Res spectroradiometer, ASD FieldSpec 3, ASD FieldSpec Pro FR spectrometer, ASD FieldSpec Pro FR spectrometer, ASD + GER 1500 spectroradiometer, Spectra Vista Corp.

MS-720 spectroradiometer, EKO Instruments Co., Ltd. FieldSpec Pro FR spectroradiometer, ASD

MSR 16R radiometer, Cropscan Inc. MSR 16R radiometer, Cropscan Inc. GreenSeeker optical sensor, Trimble Navigation

Model 505 GreenSeeker optical sensor, Trimble Navigation MSR 16 radiometer, Cropscan Inc.

M

M

ADC, Tetracam Inc.

12–1000 modular-multiband radiometer, Barnes Engineering Co. System composed of visible and NIR ‘Varispec’ liquidcrystal tunable-filters, Cambridge Research Instrumentation Inc. + Pluto digital camera, PixelVision Inc. Model 505 GreenSeeker optical sensor, Trimble Navigation

M

M

M

M

Sensor details

Cotton

Cotton

Pinto bean

Cotton

Wheat

Pepper

Cotton

Arthropod counts

2,151 + 512

Soybean

Strawberry

Damage assessments Soybean Arthropod counts Cotton

Arthropod counts

Arthropod counts

Damage assessments Pepper

Visual inspections

Damage assessments Corn

Arthropod counts

Visual inspections or Wheat controlled infestations Arthropod counts Wheat

Controlled infestations Controlled infestations

Cotton Controlled infestations or arthropod counts

Visual inspections, sooty mold assessmentsb Arthropod counts

Gossypium hirsutum

Glycine max Gossypium hirsutum

Glycine max

Fragaria × ananassa

Capsicum annuum

Capsicum annuum L.

Zea mays

Triticum aestivum

Triticum aestivum

Triticum aestivum

Phaseolus vulgaris L.

Gossypium hirsutum

Gossypium spp.

Gossypium hirsutum

Gossypium hirsutum

Plant common name Plant species

2,151 2,151

2,151

2,151

2,151

213

2

16

16

16

2

3

2

68

3

No. of spectral Field bands observations

Yang et al. 2009b Yang et al. 2005, 2009b Martin and Latheef 2019

Hemiptera: Aphididae Diuraphis noxia

Schizaphis graminum Hemiptera: Aphididae

Mirik et al. 2012

Hemiptera: Aphididae Diuraphis noxia

Cotton aphid

Silverleaf whitefly Cotton aphid

Aphis gossypii

Bemisia tabaci Aphis gossypii

Two-spotted spider Tetranychus urticae mite Soybean aphid Aphis glycines

Banks grass mite + two-spotted spider mite Chilli thrips

Mohite et al. 2018 Herrmann et al. 2012, 2015, 2017 Acari: Tetranychidae Fraulo et al. 2009 Hemiptera: Aphididae Alves et al. 2015, 2019 Hemiptera: Aleyrodidae Iost Filho 2019 Hemiptera: Aphididae Reisig and Godfrey 2006 Hemiptera: Aphididae Reisig and Godfrey 2007

Acari: Tetranychidae Oligonychus pratensis Banks + Tetranychus urticae Scirtothrips dorsalis Thysanoptera: Hood Thripidae Two-spotted spider Tetranychus urticae Acari: Tetranychidae mite

Russian wheat aphid Greenbug

Martin and Latheef 2018

Acari: Tetranychidae

Two-spotted spider Tetranychus urticae mite Two-spotted spider Tetranychus urticae mite

Martin et al. 2015, Martin and Latheef 2017, 2018 Lan et al. 2013

Fitzgerald et al. 2004

Acari: Tetranychidae

Acari: Tetranychidae

Russian wheat aphid

References

Hemiptera: Aleyrodidae Everitt et al. 1996

Tetranychus turkestani Acari: Tetranychidae

Bemisia tabaci

Order: Family

Two-spotted spider Tetranychus urticae mite

Strawberry spider mite

Silverleaf whitefly

Arthropod common name Arthropod species

Spectral resolutiona

Table 4. Studies on ground-based hyperspectral and multispectral remote sensing to detect arthropod-induced stress in crops and orchards

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GER 2600 spectroradiometer, Spectra Vista Corp. FieldSpec Pro FR spectroradiometer, ASD

H

H

FieldSpec 3 Hi-Res spectroradiometer, ASD

FieldSpec Handheld spectroradiometer, ASD GER 2600 spectroradiometer, Spectral Vista Corp. FieldSpec Handheld spectroradiometer, ASD

GER 1500 spectroradiometer, Spectra Vista Corp. GER 1500 spectroradiometer, Spectra Vista Corp. FieldSpec Pro FR spectrometer, ASD + GER 1500 spectroradiometer, Spectra Vista Corp. FieldSpec Pro FR spectrometer, ASD SE590 spectroradiometer, Spectron Engineering, Inc. ImSpector V10E imaging spectograph, Specim Spectral Imaging Ltd. Fieldspec Full Range, ASD

FieldSpec 3 Hi-Res spectroradiometer, ASD FieldSpec 3 Hi-Res spectroradiometer, ASD FieldSpec spectroradiometer, ASD FieldSpec 3 Hi-Res spectroradiometer, ASD

Sensor details

H

H

H

H

H

H

H

H

H

H

H

H

H

H

H

H

H

Spectral resolutiona

Cotton

2,151
640
2,151
512
640
512
Damage assessments Bean
Damage assessments Rice
Rice
Phaseolus vulgaris
Oryza sativa
Oryza sativa
Oryza sativa
Arthropod counts or Rice controlled infestations
Controlled infestations
Oryza sativa
Damage assessments Rice
Oryza sativa
Oryza sativa
Damage assessments, Rice visual inspections or microscope analyses Damage assessments Rice
2,151
Oryza sativa
Damage assessments Rice
Malus domestica
512
Apple
Gossypium hirsutum
Arthropod counts
Cotton
Gossypium hirsutum
Arthropod counts or Cotton presence/ absence assessments Arthropod counts
Gossypium hirsutum
Gossypium hirsutum
Gossypium hirsutum
Gossypium hirsutum
Gossypium hirsutum
Gossypium hirsutum
Cotton
Arthropod counts
Damage assessCotton ments, sooty mold assessmentsb Arthropod counts Cotton
Visual inspections

Damage assessments Cotton

Damage assessments Cotton

Plant common name Plant species

252

2,151

2,151 + 512

512

512

2,151

2,151

2,151

2,151

No. of spectral Field bands observations

Phenacoccus solenopsis Tinsley Spodoptera exigua

NA

Tetranychus spp.

Two-spotted spider Tetranychus urticae mite

Brown planthopper Nilaparvata lugens

Brown planthopper Nilaparvata lugens

Acari: Tetranychidae

Herrmann et al. 2017

Hemiptera: Delphacidae Huang et al. 2015a, Liu and Sun 2016, Tan et al. 2019 Hemiptera: Delphacidae Prasannakumar et al. 2013, 2014, Zhou et al. 2010 Hemiptera: Delphacidae Yang et al. 2007

Lepidoptera: Crambidae Huang et al. 2012a Lepidoptera: Crambidae Yang et al. 2007 Cnaphalocrocis medinalis Rice leaf folder Cnaphalocrocis medinalis Brown planthopper Nilaparvata lugens Stål

Rice leaf folder

Lepidoptera: Crambidae Liu et al. 2012, 2018

Reisig and Godfrey 2006 Acari: Tetranychidae Peñuelas et al. 1995 Lepidoptera: Crambidae Fan et al. 2017

Acari: Tetranychidae

Cnaphalocrocis medinalis Guenee

Rice leaf folder

European red mite Panonychus ulmi Koch Striped stem borer Chilo suppressalis Walker

Spider mite

Lepidoptera: Noctuidae Sudbrink et al. 2003 Lepidoptera: Noctuidae Sudbrink et al. 2003 Acari: Tetranychidae Reisig and Godfrey 2007

Hemiptera: Cicadellidae Prabhakar et al. 2011 Hemiptera: Aleyrodidae Nigam et al. 2016 Hemiptera: Prabhakar et al. Pseudococcidae 2013

NA

Chen et al. 2018

Hemiptera: Aphididae

Aphis gossypii

Trichoplusia ni Hübner Two-spotted spider Tetranychus urticae mite

Cabbage looper

Beet armyworm

Solenopsis mealybug

Whitefly

Leafhopper

Cotton aphid

References

Order: Family

Arthropod common name Arthropod species

Table 4. Continued

8 Journal of Economic Entomology, 2020, Vol. 113, No. 1

FieldSpec Pro spectroradiometer, ASD

FieldSpec 3 spectroradiometer, ASD

Nexus FT-NIR spectrometer, Thermo Nicolet Corp. HR2000 spectroradiometer, Ocean Optics Inc. HR2000 spectroradiometer, Ocean Optics Inc. Hyperspectral camera, Resonon

H

H

H

S2000 spectrometer, Ocean Optics Inc.

Pushbroom imaging spectrometer (PIS), Beijing Research Center for Information Technology in Agriculture and University of Science and Technology of China FieldSpec Pro spectroradiometer, ASD

H

H

H

FieldSpec FR spectroradiometer, ASD FieldSpec spectroradiometer, ASD

H

H

FieldSpec UV/VNIR spectroradiometer, ASD

H

H

FieldSpec Handheld Spectroradiometer, ASD Personal Spectrometer II, ASD

H

H

H

H

Sensor details

Spectral resolutiona

2,151

2,151

2,151

2,151

1,024

2,048

512

512

213

62

62

531

2,151

2,151

Sorghum

Sorghum

Triticum aestivum

Arthropod counts or Wheat controlled infestations Arthropod counts or Wheat damage assessments

Damage assessments Wheat

Wheat

Triticum aestivum

Triticum aestivum

Triticum aestivum

Damage assessments Wheat or visual inspections Arthropod counts

Triticum aestivum

Damage assessments Wheat

Triticum aestivum

Triticum aestivum

Triticum aestivum

Triticum aestivum

Sorghum bicolor

Wheat

Controlled infestations

Wheat Controlled infestations and arthropod presence confirmations Arthropod counts Wheat

Arthropod counts

Arthropod counts

Saccharum spp.

Arthropod counts Sugarcane or damage assessments Damage assessments Tomato

Sugarcane thrips

Spider mite

Wheat aphid

Wheat aphid

Wheat aphid

Wheat aphid

Wheat aphid

Greenbug

Greenbug

Sunn pest

Hymenoptera: Cephidae Nansen et al. 2009

Li et al. 2008

Li et al. 2008

Zhao et al. 2012, Luo et al. 2013a

Luo et al. 2011; Huang et al. 2012b, 2013, 2014 Yuan et al. 2014, 2017; Zhang et al. 2017 Luo et al. 2013b,c Huang et al. 2014, Shi et al. 2017

Hemiptera: Aphididae

Hemiptera: Aphididae

Hemiptera: Aphididae

Hemiptera: Aphididae Hemiptera: Aphididae

Sitobion avenae

Sitobion avenae

Sitobion avenae

Sitobion avenae Sitobion avenae

Eurygaster integriceps Hemiptera: Scutelleridae Genc et al. 2008 Puton Schizaphis graminum Hemiptera: Aphididae Riedell and Blackmer 1999 Schizaphis graminum Hemiptera: Aphididae Mirik et al. 2006a, b

Wheat stem sawfly Cephus cinctus

Greenbug

References

Zhang et al. 2008, Luedeling et al. 2009 Thysanoptera: Thripidae Abdel-Rahman et al. 2009, 2010, 2013 NA Xu et al. 2007

Acari: Tetranychidae

Order: Family

Rhopalosiphum Hemiptera: Aphididae maidis Fitch Schizaphis graminum Hemiptera: Aphididae

NA

Fulmekiola serrata Kobus

Tetranychus spp.

Arthropod common name Arthropod species

Solanum lycopersicum Leafminer L. Sorghum bicolor Corn leaf aphid

Prunus persica (L.) Batsch

Plant common name Plant species

Arthropod counts or Peach damage assessments

No. of spectral Field bands observations

Table 4. Continued

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Two-spotted spider Tetranychus urticae mite

a

M = multispectral, H = hyperspectral. A fungus not infesting the plant, but growing on the arthropod's sugary honeydew secretions. NA = information not provided.

Classification Accuracy

b

Zea mays Corn 160 Pika II hyperspectral imaging camera, Resonon H

Arthropod counts

Dichelops Hemiptera: melacanthus Dallas Pentatomidae Green belly stink bug Zea mays Corn 240 Pika II hyperspectral imaging camera, Resonon H

Controlled infestations

Acari: Tetranychidae

Riedell and Blackmer 1999 Do Prado Ribeiro et al. 2018 Nansen et al. 2010, Nansen 2012 Hemiptera: Aphididae Diuraphis noxia 512 Personal Spectrometer II, ASD H

Controlled infestations

Wheat

Triticum aestivum

Russian wheat aphid

Mirik et al. 2007 Hemiptera: Aphididae Diuraphis noxia Russian wheat aphid 2,048 S2000 spectrometer, Ocean Optics Inc. H

Arthropod counts

Wheat

Triticum aestivum

Order: Family Plant common name Plant species No. of spectral Field bands observations Sensor details Spectral resolutiona

Table 4. Continued

the plant and the soil (mixed pixels). This should be considered when analyzing the spectrum. Wherever possible, pixels that represent soil or other types of non-canopy area are excluded from data analysis. Various VIs assist in interpreting remote sensing data (Roberts et al. 2001, Xue and Su 2017, Verrelst et al. 2019). These are mainly ratios between multiple spectral bands (Glenn et al. 2008). An oftenused index is the Normalized Difference Vegetation Index (NDVI), which incorporates the ratio of NIR and visible red light. Compared to a healthy plant, an unhealthy plant will generally reflect more visible light and less NIR light. In farming, the NDVI can be used as a predictor of plant physiological status, as well as potential yield (Peñuelas and Filella 1998). NDVI has its limitations, e.g., when there is a lot of soil in the background. To solve that issue, other VIs have been developed, such as the Soil Adjusted Vegetation Index (SAVI) (Huete et al. 1988). Where these two indices are broadband indices (i.e., they can be calculated with multispectral data), hyperspectral data allows for narrowband VIs that can more precisely focus on a specific aspect. An example is the Modified Chlorophyll Absorption in Reflectance Index (MCARI), which is defined to be maximally sensitive to chlorophyll content (Daughtry et al. 2000). Xue and Su (2017) provide a review of over 100 VIs for vegetation analysis.

Classification algorithms, which could be based on the red edge and/ or VIs, can be developed to group plants based on spectral data by relating field observations to spectral measurements (e.g., 'healthy' and 'pest-infested' plants). The algorithms can be based on various statistical approaches (Lowe et al. 2017). Classification accuracy is high if data has high robustness or repeatability. Different remote sensing studies report different classification accuracies (Lowe et al. 2017). A recent study with drone-based remote sensing to detect susceptibility against green peach aphid [Myzus persicae Sulzer (Hemiptera: Aphididae)] in canola, using a multispectral sensor mounted on an octocopter, a drone with eight rotors, reported a classification accuracy of 69–100%. These values depended on experimental day, drone height above the canopy, and whether or not non-leaf pixels were removed from the dataset. In this study, aphid infestations happened naturally, and aphids were counted on selected plants for ground verification of infestations (Severtson et al. 2016a). A study

involving two-spotted spider mite-induced stress in cotton (Gossypium spp.), using a multispectral sensor mounted on a quadcopter, a drone with four rotors, reported a classification accuracy of 74–95%. These values depended on classification methods. Spider mite infestation levels were estimated based on plant damage (Huang et al. 2018). As it is hard to reach 100% accuracy, especially when data are obtained on different days, in most studies, there are certain numbers of false positives (plants are classified as infested while they are healthy) and/or false negatives (plants are classified as healthy while they are infested) (Congalton 1991, Lowe et al. 2017). Nevertheless, multiple robust classifications have been developed to detect pest problems in different agro-ecosystems, which provide good indicators for field scouting (Tables 1–4).

Drones, Remote Sensing, and Arthropod Pests Everitt et al. (2003) provided an overview of the potential use of remote sensing data collected in a manned aircraft for pest management. The authors mapped four different pest-host systems (citrus orchards, cotton crops, forests, and rangelands), and concluded that aerial photography and videography could be used to detect arthropod infestations in both agricultural and natural environments (Everitt et al. 1994, 1996). With the development of unmanned

Arthropod common name Arthropod species

References

aircrafts, it has become more affordable and practically feasible to collect aerial remote sensing data. A recent study with dronebased remote sensing to detect crop pests includes stress induced by sugarcane aphid [Melanaphis sacchari Zehntner (Hemiptera: Aphididae)] in sorghum (Sorghum bicolor (L.) Moench), using a multispectral sensor mounted on a fixed-wing drone. Aphids were counted throughout the growing season for ground verification of infestations, and damage was assessed as coverage with sooty mold, a fungus not infesting the plant, but growing on the aphids' sugary honeydew secretions (Stanton et al. 2017). Colorado potato beetle [Leptinotarsa decemlineata Say (Coleoptera: Chrysomelidae)] damage in potato (Solanum tuberosum L.) has been assessed using a multispectral sensor mounted on a hexacopter, a drone with six rotors. Plants were infested with different numbers of beetles, and insects were counted and plant damage was visually assessed for ground verification of pest infestations (Hunt et al. 2016, Hunt and Rondon 2017) (Table 1). A study by F. Iost Filho, MSc, Dr. P. Yamamoto, and collaborators at the University of São Paulo, Brazil, is analyzing the effects of stress induced by several arthropod pests in soybean fields, including silverleaf whitefly [Bemisia tabaci Gennadius (Hemiptera: Aleyrodidae)], stink bugs (Hemiptera: Pentatomidae), and caterpillars (Lepidoptera: Noctuidae). The system is composed of a drone-based multispectral sensor and a ground-based hyperspectral sensor (Iost Filho 2019). Researchers at the University of Wisconsin, WI are currently using a quadcopter equipped with a multispectral sensor to detect caterpillar damage in cranberry (Vaccinium macrocarpon Aiton) (Seely 2018). An ongoing study by Dr. E. de Lange, Dr. C. Nansen and collaborators at the University of California Davis, CA involves detection of stress induced by two-spotted spider mite in strawberry (Fragaria × ananassa Duchesne), using an octocopter equipped with a hyperspectral sensor (Fig. 4). Furthermore, aerial remote sensing can help distinguish between different non-crop plant species. If these plant species were differentially preferred as alternate hosts by important pests, remote sensing could contribute to vegetation management decisions (Sudbrink et al. 2015).

Barbedo (2019) compiled a list of drone-based remote sensing studies for various applications, including detection of pests, pathogens, drought, and nutrient deficiencies. Drones are increasingly used for remote sensing studies and are particularly cost-efficient for inspections of smaller fields (Matese et al. 2015). As technology improves and costs decrease, they may also become more competitive for use in larger fields. Ultimately, usefulness of drone-based remote sensing for detection of pest problems will depend on individual grower needs.

Distinguishing Multiple Stressors With Remote Sensing Most of the above-mentioned studies are based on a system composed of one arthropod pest species and one specific crop. However, when multiple arthropod pests are present, more advanced methods of data calibration and analysis are necessary. Prabhakar et al. (2012) inferred that damage by different pests on the same host plant requires a combination of multiple spectral bands for accurate detection. Indeed, a greenhouse study in wheat (Triticum aestivum L.) showed that

reflectance data could be used to differentiate between two different pests. Plants were experimentally infested with greenbugs [Schizaphis graminum Rondani (Hemiptera: Aphididae)] or Russian wheat aphids [Diuraphis noxia Kurdjumov (Hemiptera: Aphididae)], and insects were counted on a regular basis. The authors did mention that additional field studies would be needed, as other stressors could result in similar symptoms as aphid infestations (Yang et al. 2009b). A field study in wheat used reflectance data to differentiate between arthropod [wheat aphid, Sitobion avenae Fabricius (Hemiptera: Aphididae)] and pathogen (yellow rust, Puccinia striiformis Westend. f. sp. tritici Eriks and powdery mildew, Blumeria graminis (DC.) Speer) infestations. Aphids occurred naturally in the field, and pathogens were inoculated; for all three stressors, damage levels were estimated. Overall classification accuracy was 76% (Yuan et al. 2014). Another field study in wheat used reflectance data to distinguish between arthropod infestations

Fig. 3. Spectra of soybean leaves at different spectral resolutions. (a) As recorded by a handheld spectrometer with 1 nm spectral resolution (e.g., FieldSpec, ASD Inc., Boulder, CO). (b) Resampled to the spectral resolution of a hyperspectral imaging spectrometer (3–4 nm spectral resolution, e.g., OCI Imager, BaySpec, San Jose, CA). (c) Resampled to the spectral resolution of a multispectral sensor (four spectral bands, e.g., Parrot Sequoia, Parrot, Paris, France).

(Russian wheat aphid) and abiotic stressors (drought and agronomic conditions, possibly poor tillage, germination, or fertilization). The different stressors were verified onsite (Backoulou et al. 2011b). However, laboratory and field studies on cotton plants exposed difficulties distinguishing two arthropod pests, cotton aphid [Aphis gossypii Glover (Hemiptera: Aphididae)] and two-spotted spider mite, based on spectral signatures. In these studies, plants were experimentally infested, and insects were counted, or their presence or absence was assessed, over time (Reisig and Godfrey 2007). It also proved difficult to separate nitrogen deficiencies and aphid infestations in cotton field studies. In these studies, aphids were naturally present, and plots were treated with pesticides to increase aphid populations, presumably by killing natural enemies. Aphids were counted throughout the experimental period. Different amounts of nitrogen were applied, which was verified with soil samples and analysis of plant nitrogen uptake (Reisig and Godfrey 2010). An overview of the few studies on hyperspectral and multispectral sensors to distinguish various biotic and abiotic stressors can be found in Table 5. Spectral indices that accurately predict the presence of various arthropod pests, as well as distinguish arthropod-induced stress from other sources of stress, are required for a large number of crops in order to be widely used in precision agriculture (Mulla 2013).

Actuation Drones for Precision Application of Pesticides While sensing drones could help detect pest hotspots, actuation drones could help control the pests at these hotspots. Pest hotspots could potentially be managed through variable rate application of pesticides. Aircrafts have been used for decades for pesticide sprays, but products are deposited over large areas, and a large amount is lost to drift (Pimentel 1995, Bird et al. 1996). This is a concern for

neighboring terrestrial and aquatic ecosystems, as well as for human health (Damalas 2015). Major factors determining spray drift are droplet size (influenced by nozzle type and product formulation), weather conditions (e.g., wind speed and direction), and application method (e.g., spray height above the canopy) (Hofman and Solseng 2001, Al Heidary et al. 2014). Empirical and modeling studies showed that spray drift into non-target areas can be considerable (Woods et al. 2001, Sánchez-Bayo et al. 2002, Teske et al. 2002, Tsai et al. 2005, Al Heidary et al. 2014). Therefore, improved methods of pesticide application are highly needed (Lan et al. 2010), and there is potential for the use of drones in precision application of insecticides and miticides (Costa et al. 2012; Faiçal et al. 2014a,b, 2016, 2017; Brown and Giles 2018). Some of the aspects that give drones a competitive edge over manned crop dusters are their relative ease of deployment, reduction in operator exposure to pesticides, and potential reduction of spray drift (Faiçal et al. 2014b). Indeed, in Japan, where drones have been used in agriculture since the 1980s, drones are widely used to spray pesticides on rice, Oryza sativa L.. These drones are mostly heavier than 25 kg, but we discuss them here, as they are among the most widely used drones in pest management. Development of unmanned aerial vehicles for crop dusting started at the Japanese Agriculture, Forestry, and Fishery Aviation Association, an external organization of the Japanese Ministry of Agriculture, Forestry, and Fisheries. A prototype was completed in 1986 by Yamaha, a Japanese multinational corporation with a wide range of products and services, and the R-50 appeared on the market in

1987: the world's first practical-use unmanned helicopter for pesticide applications, with a payload of 20 kg (Miyahara 1993, Sato 2003, Yamaha 2014a, Xiongkui et al. 2017). A few successors have launched since, with greater payload capacities and simplicity of use (Yamaha 2014b, 2016). In Japan alone, as of March 2016, about 2,800 unmanned helicopters are registered

Fig. 4. Airborne remote sensing in California strawberry. Researchers from the University of California Davis obtain canopy reflectance data of arthropodinfested plants with a drone-mounted hyperspectral sensor in a commercial strawberry field.

M

H

H

H

H

H

H

M

M

M

M

M+H

M+H

M

M

M

Platform

Ground-based

Ground-based

Ground-based

Ground-based

Ground-based

Ground-based

Ground-based

Aerial – manned aircraft

Aerial – manned aircraft

Aerial – manned aircraft

Aerial – manned aircraft

Aerial – Manned aircraft

Aerial – manned aircraft

Orbital

Orbital

Orbital

Landsat-8, NASA

QuickBird, DigitalGlobe

QuickBird, DigitalGlobe

SAMRSS + AVNIR, Opto-Knowledge Systems SAMRSS + AVNIR, Opto-Knowledge Systems

MS3100, DuncanTech

MS3100, DuncanTech

MS3100, DuncanTech

MS3100, Duncan Tech

FieldSpec, FieldSpec Pro, or FieldSpec UV/ VNIR, ASD

FieldSpec Handheld, ASD Personal Spectrometer II, ASD

FieldSpec Pro FR, ASD + GER 1500, Spectra Vista Corp.

FieldSpec Pro FR, ASD

MSR 16R, Cropscan Inc. Pika II, Resonon

Sensor details

9

3

3

4 + 60

4 + 60

3

3

3

3

2,151

512

512

2,151 + 512

2,151

160

16

No. of spectral bands

Wheat

Cotton

Cotton

Cotton

Cotton

Wheat

Wheat

Wheat

Wheat

Wheat

Wheat

Rice

Cotton

Cotton

Corn

Wheat

Plant common name

Wheat aphid

Cotton aphid

Cotton aphid

Cotton aphid

Cotton aphid

Greenbug

Russian wheat aphid

Russian wheat aphid

Russian wheat aphid

Wheat aphid

Russian wheat aphid

Brown planthopper

Cotton aphid

Two-spotted spider mite Cotton aphid

Russian wheat aphid

Stress 1

Damage assessments

Visual inspections Visual inspections -

2013 Visual inspections Visual inspections Backoulou et al. 2011a, b Visual inspections Visual inspections Backoulou et al.

Damage assessments

Visual inspections Visual inspections Visual inspections Visual inspections

-

Other factorsb Drought stress Agronomic conditionsc Drought stress Agronomic -

-

Powdery mildew

-

Nitrogen stress -

Spider mite

conditionsc

Powdery mildew

-

Nitrogen stress -

Spider mite

Greenbug

Yellow rust

Greenbug

Nitrogen stress -

-

-

Different fertilizer levels, soil samples, plant nutrient uptake analysis Arthropod counts Different fertilizer levels, soil samples, plant nutrient uptake analysis Damage assessments

Arthropod counts

Arthropod counts

Arthropod counts

Arthropod counts

Arthropod counts -

Arthropod counts

Controlled infestations

Arthropod counts

Damage assessments

Arthropod counts or presence/ absence assessments Different fertilizer levels Controlled infest- ations

Arthropod counts

Two-spotted spider mite

Spider mite

Arthropod counts

Different irrigation levels Arthropod counts -

Ma et al. 2019

2010

2006 Reisig and Godfrey

Reisig and Godfrey

2010

Reisig and Godfrey

2006

2015 Reisig and Godfrey

2016 Backoulou et al.

Blackmer 1999 Huang et al. 2014; Yuan et al. 2014, 2017, Shi et al. 2017, Zhang et al. 2017 Backoulou et al.

Riedell and

Huang et al. 2015a

2007

2006 Reisig and Godfrey

Nansen et al. 2010, Nansen 2012 Reisig and Godfrey

Yang et al. 2009b

Arthropod counts

-

Drought stress -

Greenbug

Arthropod counts -

References

Arthropod counts

Field observations 3

Field observations 2

Stress 3

Field observations 1

Stress 2

names are mentioned there.

b

a

M = multispectral, H = hyperspectral. Incl. damage caused by drought or poor fertilization. c Incl. damage caused by poor fertilization, germination, or tillage. Only studies involving at least one arthropod pest are included in this table. Studies mentioned in this table are also included in Tables 2–4; plant and arthropod species

Spectral resolutiona

Table 5. Studies on hyperspectral and multispectral remote sensing to distinguish various biotic and abiotic stressors in crops

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14

Actuation Drones for Precision Releases of Natural Enemies Biological control is a potential sustainable alternative to pesticide use. It is the use of a population of one organism to decrease the population of another, unwanted, organism (Van Lenteren et al. 2018). Biological control organisms include, but are not limited to, parasitoids, predators, entomopathogenic nematodes, fungi, bacteria, and viruses. A large variety is commercially available. Drones may be a particularly useful tool for augmentative biological control, which relies on the large-scale release of natural enemies for immediate control of pests (Van Lenteren et al. 2018). They could distribute the natural enemies in the exact locations where they are needed, which may increase biocontrol agent efficacy and reduce distribution costs. Some natural enemies, such as insect-killing fungi and nematodes, can be applied with conventional spray application equipment (Shah and Pell 2003, Shapiro-Ilan et al. 2012). Therefore, these biocontrol agents could potentially be applied by drones as described above for pesticides (Berner and Chojnacki 2017). However, application of other natural enemies is often costly and time-consuming. For example, the predatory mite Phytoseiulus persimilis Athias-Henriot (Acari: Phytoseiidae), an important natural enemy of the worldwide pest two-spotted spider mite, is available in bottles mixed with the mineral substrate vermiculite, and the recommended way of dispersal is by sprinkling contents onto individual plants (e.g., Koppert 2017a, Biobest 2018). Phytoseiulus persimilis has such a high level of specialization that populations

succumb when no prey is present (McMurtry and Croft 1997, Cakmak et al. 2006, Gerson and Weintraub 2007, Dara 2014). Various mechanical distribution systems have been developed to facilitate predator dispersal, such as the Mini-Airbug, a handheld appliance with a fan (Koppert 2017b), as well as other devices (Giles et al. 1995, Casey and Parrella 2005, Opit et al. 2005). Growers in Brazil are known to use dispensers attached to motorbikes (Parra 2014, Agronomic Nordeste 2015), but this could potentially damage the crop. Release of natural enemies by aircraft was proposed in the 1980s (Herren et al. 1987, Pickett et al. 1987), but small drones would offer myriad possibilities. Coverage of larger areas compared to manual distribution, reducing application costs per acre, potentially increases the use of natural enemies in favor of pesticide sprays. Development of drone-mounted dispensers has mainly focused on two types of natural enemies: predatory mites such as the above-mentioned P. persimilis, and parasitoid wasps such as the eggparasitoid Trichogramma spp. (Hymenoptera: Trichogrammatidae). To combat two-spotted spider mite, an important pest of a large number of crops worldwide, a California-based company is offering services to distribute predatory mites

using drones, on crops such as strawberry (Parabug 2019). An Australia-based company also uses drones to distribute predatory mites on strawberry crops (Drone Agriculture 2018). At the University of Queensland in Australia, a drone-mounted device is being developed to distribute predatory mites in corn (Pearl 2015). At the University of California Davis, Dr. Z. Kong and Dr. C. Nansen, in collaboration with aerospace engineering students, have developed a platform for drone-based distribution of predatory mites, BugBot (Teske et al. 2019) (Fig. 5). They are currently testing the prototype and accompanying software, to optimize natural enemy releases. We propose that collaboration between growers, agricultural scientists, aerospace engineers, and software programmers is key in developing a product that is effective and user-friendly. Trichogramma spp. parasitoids are important biocontrol agents of European corn borer [Ostrinia nubilalis Hübner (Lepidoptera: Crambidae)], a major pest of sweet corn in the United States and Europe (Smith 1996). Various companies and research institutes all over the world have started Trichogramma drone applications, including Austria, Germany, France, Italy, and Canada (e.g., Chaussé et al. 2017, Airborne Robotics 2018). Drone-released Trichogramma parasitoids are also deployed in China for control of pests in sugarcane (Saccharum spp.) (Li et al. 2013, Yang et al. 2018). In Brazil, drone applications of Trichogramma spp., as well as the parasitoid Cotesia flavipes Cameron (Hymenoptera: Braconidae), are employed to combat the sugarcane borer [Diatraea saccharalis Fabricius (Lepidoptera: Crambidae)] in sugarcane. Trichogramma spp. are also employed against various other lepidopteran pests in other crops (Parra 2014, Rangel 2016, Xfly Brasil 2017). While we did not address pest management in forestry settings in this review, a recent report by Martel et al. (2018) deserves to be mentioned, as it is the first to compare drone release and ground release of natural enemies. The report evaluated the efficacy of Trichogramma spp. to combat spruce budworm [Choristoneura fumiferana Clemens (Lepidoptera: Tortricidae)], an important pest of fir and spruce trees in Canada and the United States. Drone releases, using Trichogrammaparasitized host eggs mixed with vermiculite, were compared to ground releases, using commercially available cards containing parasitized eggs of Mediterranean flour moth [Ephestia kuehniella Zeller (Lepidoptera: Pyralidae)]. Data were collected in two locations in Quebec, Canada. In one of these locations, drone release resulted in similar spruce budworm egg parasitism rates as ground release of natural enemies. Results for the other location were inconclusive, as

for operation, spraying more than a third of the country's rice fields. The use of unmanned crop dusters has also spread to other crops, such as wheat, oats, and soybean, and the number of crops continues to expand (Yamaha 2016). Japanese unmanned crop dusters are also employed in South Korea (Xiongkui et al. 2017) and are currently being tested for spraying of pesticides in California vineyards (Bloss 2014, Giles and Billing 2015, Gillespie 2015). On a small but increasing scale, unmanned crop dusters are used in China, for crops such as rice, mango, and plantain (Zhou et al. 2013, Tang et al. 2016, Xiongkui et al. 2017, Lan and Chen 2018, Yang et al. 2018, Zhang et al. 2019). Novel types of unmanned crop dusters and/or novel spray rigs fitting commercially available drones are currently being developed in China (Ru et al. 2011, Xue et al. 2016, Xiongkui et al. 2017), South Korea (Shim et al. 2009), the United States (Huang et al. 2009), Ukraine (Pederi and Cheporniuk 2015, Yun et al. 2017), and Spain (Martinez-Guanter et al. 2019), among other places. Recently, smaller drone-based crop dusters appeared on the market, such as the DJI AGRAS MG-1S with a 10 kg payload (DJI 2019). A collaboration between Japan's Saga University, Saga Prefectural Government Department of Agriculture, Forestry, and Fisheries, and OPTiM Corporation resulted in AgriDrone, a small drone that can pinpoint pesticide application. Interestingly, AgriDrone is also equipped with an UV bug zapper, recognizing and killing over 50 varieties of nocturnal agricultural pests at nighttime (OPTiM 2016). However, no peer-reviewed literature on this system has appeared since its announcement. Current research focuses on improved spray coverage, to enable large-scale adoption of drones for application of pesticides (Qin et al. 2016, Wang et al. 2019a, Wang et al. 2019b). In combination with precision monitoring, precision application of pesticides could reduce the overall number of sprays, contributing to reduced pesticide use and decreased development of resistance, as well as increased presence of natural enemies (Midgarden et al. 1997).

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egg parasitism rates were negligible. Drone releases were reportedly faster than ground releases of natural enemies. Although more studies are necessary, these preliminary results show the high potential of drone-based Trichogramma distribution in forests, especially on small scales, and in conditions under which

insecticide applications are not appropriate (Martel et al. 2018). It is important to perform similar studies in field crops and orchards, to evaluate the efficacy of drone-released natural enemies. Other types of natural enemies can be drone-applied as well, such as green lacewing, [Chrysoperla spp. (Neuroptera: Chrysopidae)] and minute pirate bug [Orius insidiosus Say (Hemiptera: Anthocoridae)] to control aphids and thrips, and mealybug destroyer [Cryptolaemus montrouzieri Mulsant (Coleoptera: Coccinellidae)] to control mealybugs (Parabug 2019). Researchers at the University of Southern Denmark, in collaboration with Aarhus University, are currently developing a dispensing mechanism for ladybirds and other important natural enemies of aphids (SDU 2018). EWH BioProduction, a producer of beneficial organisms (EWH BioProduction 2019), is also involved in this EcoDrone project, as well as Ecobotix, a company offering drone-based services, which is developing a separate solution for dispensing natural enemies (Ecobotix 2018). Dronebased dispensers could be adapted or newly developed for other types of beneficial arthropods as well. Thus far, little to no peer-reviewed research exists on the efficacy of these operations. Therefore, this is a call for additional research. It is of utmost importance to verify that natural enemies distributed by drones are not damaged during transport and distribution and are still effective as biological control agents. Also, it is necessary to develop hardware and software mechanisms that can precisely distribute the natural enemies in different weather conditions, particularly considering that wind is a crucial factor for the distribution. Individual drone-mounted dispensers all use different technologies, which could be compared to optimize natural enemy distribution. This could pave the way for larger-scale operations of this promising resource.

Novel Uses for Drones in Precision Pest Management Pest Outbreak Prevention Sensing and actuation drones could potentially contribute to the prevention of pest outbreaks. Plants exposed to abiotic stressors, such as drought and nutrient deficiencies, are often more susceptible to biotic stressors. This holds true for a large variety of arthropod pests, such as spider mites (Garman and Kennedy 1949, Rodriguez and Neiswander 1949, Rodriguez 1951, Perring et al. 1986, Stiefel et al. 1992, Machado et al. 2000, Abdel-Galil et al. 2007, Chen et al. 2007, Nansen et al. 2013, Ximénez-Embún et al. 2017), aphids (Myers and Gratton 2006, Walter and Difonzo 2007, Lacoste et al. 2015), and lepidopteran larvae (Gutbrodt et al. 2011, 2012; Grinnan et al. 2013; Weldegergis et al. 2015). Due to this well-established association between abiotic stressors and risk of arthropod pest outbreaks, it may be argued that precision application of abiotic stress relief, such as application of water and fertilizer, represents a meaningful approach to reducing the risk of outbreaks by some arthropod pests (Nansen et al. 2013, West and Nansen 2014). Indeed, pest management focus could shift from being based mainly on responsive insecticide applications to a more preventative approach in which maintaining crop health is the main focus (Culliney and Pimentel 1986, Altieri and Nicholls 2003, Zehnder et al. 2007, Amtmann et al. 2008, West and Nansen 2014). Use of sensing and actuation drones could contribute to this shift, by assessing plant stress status, and preventative applications of water and fertilizers. To the best of our knowledge, drones have thus far not been deployed for precision irrigation purposes, and although drones are on the market that advertise the capacity to apply liquid or granular fertilizers, there is no peer-reviewed literature on their use. Many current spray tractors contain options for variable rate applications of nutrients, for an adequate response to deficiencies detected with remote sensing (Raun et al. 2002). However, there would be myriad opportunities for use of drones in this respect, due to their maneuverability and capacity to treat small areas.

Fig. 5. Prototype of BugBot predatory mite dispenser. BugBot, developed by mechanical and aerospace engineering students at the University of California Davis, is a drone-mounted dispenser that can distribute predatory mites, important biological control agents of spider mites. In the picture, the BugBot dispenses vermiculite, the mineral substrate the predators can be obtained in.

Reducing Pest Populations: Sterile Insect Technique and Mating Disruption

Challenges and Opportunities Major challenges for the use of drones in precision agriculture are the costs of drones and associated sensors and material, limited flight time and payload, and continuously changing regulations. For a more comprehensive review of challenges and opportunities of drones in precision agriculture and environmental studies, two fields that share similar uses of drones, see Hardin and Jensen (2011), Zhang and Kovacs (2012), Whitehead and Hugenholtz (2014), and Whitehead et al. (2014). We here focus specifically on the technical challenges for the use of drones in precision pest management, and highlight recent changes in regulations.

Costs A major challenge for the use of drones in precision pest management is the initial steep costs of the material: the drone itself, the various sensors or application technologies, mounting equipment, and analysis software. Although costs are decreasing with improving technology, sums are still relatively high. In 2017, costs of a fixed-wing drone with hyperspectral sensor were estimated at €120,000 ($144,000), while costs of a multi-rotor drone with a multispectral sensor were estimated at €10,000 ($12,000) (Pádua et al. 2017). Therefore, various companies are offering drone-related services, such as renting out drones with remote sensing equipment (e.g., Blue Skies 2019) or offering predator dispersal services (e.g., Parabug 2019). Also, consulting companies offer remote sensing and data analysis services for a reasonable fee, even combined with other agriculture-related services, to provide one platform for efficient record-keeping and planning (e.g., UAV-IQ 2018).

Pest Population Monitoring

Data Collection, Analysis, and Interpretation

Drones could also be used to track populations of mobile insects that can be equipped with transponders, such as locusts (Tahir and Brooker 2009). A recent paper by Stumph et al. (2019) described the use of drones equipped with a UV light source and a video camera to detect fluorescent-marked insects. Brown marmorated stink bugs [Halyomorpha halys Stål (Hemiptera: Pentatomidae)], 13–16 mm long, were coated in red fluorescent powder, and placed in a grass

Concerning sensing drones, repeatability of remote sensing data is a recurring issue. Canopy reflectance varies depending on solar angle, cloud coverage, and various other factors. Therefore, it is difficult to compare data obtained on a specific day with data obtained the next day, even the next hour. Novel methods for calibration and processing of drone-based remote sensing data are continuously being developed (Bourgeon et al. 2016, Singh and Nansen 2017,

A potential new area for use of drones in pest management is the release of sterile insects. Codling moth [Cydia pomonella L. (Lepidoptera: Tortricidae)] is a major problem in apple orchards (Malus domestica Borkh.) (Judd and Gardiner 2005), and pilot programs to release sterile insects with drones have been successful in controlling codling moth populations in New Zealand, Canada, and the United States (DuPont 2018, M3 Consulting Group 2018, Seymour 2018, Timewell 2018). Furthermore, pilot programs for control of pink bollworm [Pectinophora gossypiella Saunders (Lepidoptera: Gelechiidae)] in cotton, and Mexican fruit fly [Anastrepha ludens Loew (Diptera: Tephritidae)] in citrus, with drone-released sterile insects proved effective for control of these pests in the United States (Rosenthal 2017). Similarly, false codling moth [Thaumatotibia leucotreta Meyrick (Lepidoptera: Tortricidae)] could successfully be controlled in citrus orchards in South Africa (FlyH2 Aerospace 2018). The sterile insect technique (SIT) produces sterile or partially sterile insects through irradiation. After mating with wild insects, there is either no offspring, or the resulting offspring is sterile, resulting in reduced pest populations. SIT is environmentally friendly, species-specific, and compatible with other management methods such as biological control, making it an important IPM tool (Simmons et al. 2010). Drone release of the sterile insects may be cheaper and faster than ground release, which occurs for instance by means of all-terrain vehicles (ATVs), or release by manned aircraft (Tan and Tan 2013). For sterile codling moth, drone-dispersal may also improve moth performance. Drones release the moths above the canopy whereas ATVs release them on the orchard floor. Codling moth prefer to mate in the upper one-third of the canopy, thus drone release may facilitate the moths reaching their preferred habitat, while minimizing biotic and abiotic mortality factors. Irradiated moths must be kept chilled during transportation prior to orchard dispersal to prevent damage and scale loss. An optimized delivery system from the rearing facility to the orchard may increase the sterile moths' effectiveness in mating with wild moths (DuPont 2018, Dr. E. Beers, personal communication). Therefore, drone releases may make SIT more widely available. Drones could also be deployed to place mating disruptors such as SPLAT (specialized pheromone & lure application technology) in commercial fields (FlyH2 Aerospace 2018). SPLAT is an inert matrix which can be infused with pheromones and/or pesticides and is applied as dollops (ISCA 2019a, b). Mating disruption relies on the release of pheromones, which interferes with mate finding (Miller and Gut 2015), while attract-and-kill involves an attractant and a killing agent (Gregg et al. 2018). A combination of these methods effectively control various pests in a number of cropping systems, including blueberry (Vaccinium corymbosum L.) and cranberry (Rodriguez-Saona et al. 2010, Steffan et al. 2017). Researchers from the University of Wisconsin are currently

developing a drone release mechanism for SPLAT, to improve IPM practices in cranberry (Miller 2015, Chasen and Steffan 2017, Seely 2018).

field. Drone data were obtained at night, and specific software was developed to visualize individual insects. This system provides a relatively fast alternative for manual, time-consuming, mark-releaserecapture studies. Although insects still need to be coated initially, the method eliminates the need to physically recapture the insects. Also, it removes the need for destructive sampling, so that insects could potentially be sampled over a longer time period. Thus, use of this novel, drone-based system could improve efficiency and cost-effectiveness of mark-release-recapture studies of insect migration (Stumph et al. 2019). Furthermore, drones could be used to collect pest specimens for monitoring (Shields and Testa 1999, Kim et al. 2018), or to survey for pests, such as Asian longhorned beetles [Anoplophora glabripennis Motschulsky (Coleoptera: Cerambycidae)], in tall trees, assisting tree climbers (Rosenthal 2017). A recent review has even suggested the use of drones for collection of plant volatiles (Gonzalez et al. 2018). Indeed, plant volatiles induced in response to herbivory could indicate the presence of specific pests (Turlings and Erb 2018, De Lange et al. 2019), and drone-based volatile collections have been deployed for air quality measurements (Villa et al. 2016). Development of novel sensors and technology will undoubtedly open the door to various other uses of drones in agricultural pest management.

Flight Time and Payload Concerning both sensing and actuation drones, flight time and payload are among the most limiting factors for use of drones in agriculture. Although individual drones can have payloads of 24 kg and up (Yamaha 2016), it would be challenging, though not impossible to develop a drone that can both detect pest hotspots and apply solutions. Indeed, the above-mentioned AgriDrone can both detect pest hot spots and apply localized solutions (OPTiM 2016). However, to cover large areas, using a network of communicating drones, or swarm, may eventually be most efficient (Stark et al. 2013a, Faiçal et al. 2014a, Gonzalez-de-Santos et al. 2017). Ultimately, one or multiple sensing drones detecting pest hotspots will communicate with one or multiple actuation drones dispensing biological control organisms or agrochemicals exactly where needed; they can also autonomously fly back to their base stations to recharge, without further human intervention. Establishing drone swarms is an active research area in the drone community (Bertuccelli et al. 2009, Alejo et al. 2014, Ponda et al. 2015). However, how to translate these techniques into the pest management application domain is still an open question.

Adverse Weather Conditions and Other Environmental Factors Adverse weather conditions could limit sensing and actuation drone activity. Most drones have an optimal operating temperature range.

Strong wind could interfere with obtaining aerial remote sensing data, as well as with pesticide or biocontrol dispersal. Ideally, remote sensing measurements should be taken all under the same solar and sensor angle geometry, to avoid differences due to the effect that natural surfaces scatter radiation unequally into all directions (Weyermann et al. 2014). Data acquisition with a clear, cloudless sky, at solar noon reduces shadow influences as well as variations between measurements due to changing light intensity resulting from cloud cover (Souza et al. 2010). However, these conditions cannot be easily obtained in farms all over the world. Clouds and fog limit drone flights, and it is not recommended to fly a drone in rain or snow conditions, or during thunderstorms. Other environmental factors limiting drone activity are differences in elevation within fields or orchards, and presence of wildlife, such as birds (Park et al. 2012).

Rules and Regulations In the United States, Federal Aviation Regulations (FARs) are in place for the commercial and research use of drones, prescribed by the FAA. Until 2016, a manned aircraft pilot license was necessary to fly a drone, which is costly to obtain and maintain. As of August 2016, a less stringent remote pilot license became available to operate small drones, which made commercial drone use much more readily available (FAA 2016). However, the regulations are regularly updated, which requires that pilots keep continuous track of current regulations. A few basic rules in the United States include that the pilot in command must keep a visual line of sight (VLOS) on the drone at all times. Consequently, flying is only allowed at daylight hours. Drones must fly at an altitude at or below 400 feet (122 m), at a speed at or below 100 mph (161 km/h). They are not allowed to fly over people that are not involved in the specific drone operation, and must always yield right of way to larger aircraft, including manned aircraft. Waivers from these regulations, for instance to fly at nighttime, can be requested through the FAA. Importantly, the pilot in command must perform a pre-flight check before each flight, to ascertain that the drone is in good condition for safe operation (FAA 2018b). In the United States, drones for both commercial and private use must be registered through the FAA. Regulations for

operating and registering a drone may vary in different countries, so international collaborators must make sure to follow the proper rules (Cracknell 2017, Stöcker et al. 2017). In Brazil, where drones are regularly used in precision agriculture (Jorge et al. 2014, Parra 2014), the use of drones for civil and agricultural means was regulated as recently as May 2017 by the National Agency of Civil Aviation (ANAC) (Agência Nacional de Aviação Civil 2017). Ultimately, when drones become more mainstream, general rules may become more standardized.

Communication With Growers Importantly, increased use of drones in commercial agricultural operations will not happen without adoption of the technology by growers, and they will only adopt technology that is proven to work, cost-effective, and compatible with established practices (Aubert et al. 2012, Pierpaoli et al. 2013). Extensive communication and collaboration between scientists, industry professionals, and commercial growers is needed to provide the best performing technology that tailors to growers' needs (Larson et al. 2008, Lindblom et al. 2017). Extension agents, dedicated to the translation of scientific research to practical applications, may facilitate these connections, through training and dialogue.

Aasen et al. 2018). Improved repeatability will render these data more useful for precision detection of pest problems. Data analysis is also an important challenge. Each mission with a hyperspectral sensor typically results in multiple terabytes of data, which must be properly stored, processed with specific software, and analyzed by experts with years of experience. As a result, there is an important time lag between data collection and the visibility of results. Processing of multispectral data is currently much faster than processing of hyperspectral data, but the results are less precise in terms of detection of pest problems (Yang et al. 2009a). Ultimately, automation of data analysis will improve the usability of detailed hyperspectral datasets by growers directly, leading to a timelier detection and possible response to the discovery of pest hotspots. Also, automated data analysis will facilitate communication between sensing and actuation drones, so that an actuation drone can immediately be deployed to provide solutions. Or, a single drone could function simultaneously as sensor and actuator, and directly apply solutions where necessary (Fig. 1). Concerning actuation drones, peer-reviewed research has just started to emerge, with many challenges to be overcome. One major challenge is that, in order to develop an effective actuation drone system, knowledge and expertise from multiple fields must be integrated. First, knowledge from agricultural scientists will be needed to answer research questions such as where, when, and how much of the solutions (e.g., pesticides and natural enemies) should be applied in an agricultural field. Second, engineers and software developers will need to convert such knowledge into the design of hardware and software components for the effective and efficient distribution of the solutions. Another technical challenge is the automation of the distribution of solutions. Considering the complicated and varied field and weather conditions, preferentially, users should not be asked to set up all the software parameters by themselves. Instead, the drone should be able to compute and implement the optimal distribution strategy automatically (potentially being given a digital map built by sensing drones). (Fig. 1)

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Conclusion Drones are becoming increasingly adopted as part of precision agriculture and IPM. Drones with remote sensing equipment (sensors) are deployed to monitor crop health, map out variability in crop performance, and detect outbreaks of pests. They could serve as decision support tools, as early detection and response to suboptimal abiotic conditions may prevent large pest outbreaks. When outbreaks do occur, different drones (actuators) could be deployed to deliver swift solutions to identified pest hotspots. Automating pesticide applications and/or release of biological control organisms, through communication between sensing and actuation drones, is the future. This approach requires multi-disciplinary research in which engineers, ecologists, and agronomists are converging, with enormous commercial potential.

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9. Drone Operator FAQs

agricultural drone operator FAQs — drone cost, earnings per acre, acres covered per day, batteries required, battery life, operating costs, maintenance, pilot charges and certification

In this section: Drone operator FAQs

Drone operator FAQs

Drone related FAQs

- How much does an agricultural drone cost?
- Entrylevel spraying drones: ₹3–5 lakh (small payload, 10–15 liters).
- Medium category (16–40 liters): ₹7–12 lakh.
- Advanced BVLOSready drones: ₹12–18 lakh.
- Costs vary by payload, battery system, and certification.
- How much can a drone earn per acre?
- Service providers typically charge ₹500–700 per acre for spraying.
- Net earning depends on fuel, labor, and battery costs, but margins are strong compared to manual spraying.
- How many acres can a pilot cover?
- A trained pilot can cover 15–25 acres per day with a mediumpayload drone.
- With multiple batteries and efficient refilling, coverage can reach 30–40 acres/day.
- How many batteries are required?
- Minimum 3–4 batteries per drone for continuous spraying.
- Each battery supports 20–30 minutes of flight, so rotation is essential.
- What is the battery life?
- Each battery lasts 250–300 charge cycles.
- In practice, this equals 8–12 months of heavy spraying use before replacement.
- What are operating costs?
- Battery replacement: ₹8,000–25,000 each.
- Spare parts: motors (₹2,000–10,000), propellers (₹500–2,000), frames (₹5,000–20,000).
- Annual maintenance: ₹50,000–1 lakh depending on usage.
- Consumables: pesticides/nutrients as per crop requirement.
- What maintenance is required?
- Regular cleaning of nozzles and filters.
- Firmware updates for GPS and autopilot.
- Motor and propeller checks every 100 hours.
- Battery health monitoring and safe storage.
- How much does a pilot charge?
- Certified pilots charge ₹1,500–2,500 per day.
- In contract spraying, charges are bundled into peracre service fees.
- What certifications are required?
- DGCA Remote Pilot Certificate (RPC) for medium category drones.
- DGCA Type Certification for the drone model.
- CIB&RC approval for aerial pesticide formulations.
- Insurance policy linked to drone UIN.

- How can pilots get customers?
- Partner with farmer producer organizations (FPOs) and cooperatives.
- Register with state agriculture departments for subsidy programs.
- Offer demo spraying in villages to build trust.
- Use digital platforms and WhatsApp groups for farmer outreach.
- Collaborate with agriinput companies for bundled spraying services.

Source: `Drone operator FAQs.docx` · Google Drive file id `1Dxc0FB5Tqlw9z8HmGafQU7QTp8Ux2O4c` · folder “9. Drone operator FAQs”

Appendix A — Source Brief

The original collection brief for this knowledge base.

1. Agricultural Drone Information

Collect and organize information about:

- Agricultural drones
- Drone spraying technology
- Drone capacities
- Tank capacities
- Flight time
- Battery capacity
- Coverage per days
- Spray width
- Nozzle types
- Water consumption
- Charging time
- Operating requirements
- Advantages and limitations

Output: Excel/Google Sheet with source links.

2. Drone Spare Parts

Research and collect information about commonly used spare parts:

- Batteries
- Chargers
- Motors
- Propellers
- Pumps
- Nozzles
- Flow meters
- Pipes/tubes
- Landing gear
- Controllers
- Remote controls
- Spray tanks
- Other important components

3. Drone Battery Information

Create a dedicated database for drone batteries.

Collect:

- Battery type
- Voltage
- Capacity
- Charging time
- Approximate flight time
- Cycle life
- Price
- Compatible drones
- Manufacturer
- Maintenance requirements
- Safety information
- Source

4. Crop-Wise Drone Spraying Information

For each major crop, collect:

- Major growing states
- Major growing districts
- Common pest/disease problems
- Common spraying requirements
- Products commonly applied
- Suitable drone application information
- Recommended spray volume where reliably available
- Number/timing of applications where reliably available
- Relevant government/agricultural-university information
- Sources

5. State-Wise Agricultural Information

Create a database for each Indian state.

Collect:

- Major crops
- Major agricultural districts
- Major farming seasons
- Major crop-protection challenges
- Drone adoption information
- Government drone schemes
- Agricultural universities
- Important agriculture departments
- FPOs/cooperatives where relevant
- Major agri-input markets

6. Government Schemes & Subsidies

Collect information about:

- Agricultural drone subsidies
- Government drone schemes
- Central government schemes
- State government schemes
- Farmer subsidies
- FPO schemes
- Custom Hiring Centres
- Drone entrepreneur schemes
- Women farmer/drone initiatives
- Drone pilot/operator schemes

7. Drone Regulations

Collect and organize information related to:

- DGCA rules
- Drone categories
- Pilot requirements
- Remote pilot certification
- Drone registration
- Digital Sky
- No-fly/restricted zones
- Agricultural spraying requirements
- Insurance
- Operational requirements
- State-specific requirements

Again, maintain the official source link for every important piece of information.

8. Agricultural University Research

Research publications and recommendations from:

- ICAR
- State Agricultural Universities
- Agricultural research institutions
- KVKs
- Government agriculture departments

Collect information related to:

- Drone spraying
- Spray technology
- Crop protection
- Spray volume
- Drone efficiency
- Field trials
- Pest/disease management
- New agricultural technologies

9. Drone Operator FAQs

Collect questions from the operator perspective:

- How much does an agricultural drone cost?
- How much can a drone earn per acre?
- How many acres can a pilot cover?
- How many batteries are required?
- What is the battery life?
- What are operating costs?
- What maintenance is required?
- How much does a pilot charge?
- What certifications are required?
- How can pilots get customers?

Source: `Remaining Tasks.docx` · Google Drive file id `13a57W-lN8lOv3H3tVz6ZIX_nix7kJQlf`