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Sneha Katherine
M.Sc. Entomology, Chaudhary Charan Singh Haryana Agricultural University, Hisar, Haryana, India

Swadhin Kumar Swain
M.Sc. (Ag.) Nematology, College of Agriculture, OUAT, Bhubaneswar, Odisha, India

Chinmoy Deori
Subject Matter Specialist, Agronomy, Krishi Vigyan Kendra, Sribhumi, Assam, India

Suraksha M Gouli
M.Sc. (Agri.) Scholar, Department of Sericulture, University of Agricultural Sciences, GKVK, Bengaluru, Karnataka, India

Dr. KS Pagire
Assistant Professor, Department of Entomology, College of Agriculture, Sonpur- Gadchiroli, Dr. PDKV, Akola, Maharashtra, India

Bhaswati Saikia
M.Sc. (Ag.) Entomology, College of Agriculture, Assam Agricultural University, Jorhat, Assam, India

Tejas Ashok Bhosale
Teaching Personnel, VCSG Uttarakhand University of Horticulture and Forestry Bharsar, Uttarakhand, India

Dr. Avinash Chauhan
Scientist, Department of Entomology, School of Agricultural Sciences, Nagaland University, Medziphema, Chumoukedima, Nagaland, India

Narpat Choudhary
Sacha Mitra Foundation, (Inana) Nagaur, Rajasthan, India

Bhavesh Choudhary
College of Fisheries, Central Agricultural University (Imphal), Lembucherra, Agartala, Tripura, India

Corresponding Author:
Swadhin Kumar Swain
M.Sc. (Ag.) Nematology, College of Agriculture, OUAT, Bhubaneswar, Odisha, India

Drones and AI in insect surveillance: Transforming pest forecasting systems

Sneha Katherine, Swadhin Kumar Swain, Chinmoy Deori, Suraksha M Gouli, KS Pagire, Bhaswati Saikia, Tejas Ashok Bhosale, Avinash Chauhan, Narpat Choudhary and Bhavesh Choudhary

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Abstract
Insect pests pose a severe threat to global food security, with estimated losses of 20-40% of crop yields each year. Traditional monitoring relies on manual scouting and simple weather models, often reacting too late to prevent damage. In contrast, modern systems combine Unmanned Aerial Vehicles (drones) with artificial intelligence (AI) to create rapid, high-resolution insect surveillance and forecasting. Drones equipped with advanced sensors (multispectral, thermal, RGB cameras, etc.) survey fields and orchards, while AI algorithms process the imagery and sensor data to identify pests and predict infestation trends. This synergy enables early outbreak detection and automated alerts, allowing farmers to target only affected areas and significantly reduce pesticide use. In this article, we review the theoretical foundations of AI-based image recognition and sensor data analysis, and we describe the latest drone monitoring platforms. We then examine practical applications in India and worldwide, showing how AI-enabled drones improve pest forecasting and crop protection. The benefits improved yields, resource efficiency, and faster response are highlighted, along with current challenges such as technical and regulatory hurdles. Finally, we discuss future trends in precision agriculture, illustrating how emerging drone-AI innovations will further enhance integrated pest management systems.

Keywords: Drones (UAV), artificial intelligence (AI), pest forecasting, insect surveillance, precision agriculture, integrated pest management (IPM), computer vision, crop monitoring

Introduction
Insect pests pose one of the greatest threats to global food production, especially as climate change and intensive farming have allowed outbreaks to become more frequent and severe [6]. The Food and Agriculture Organization (FAO) estimates that pests and diseases destroy roughly 20-40% of the world's crop yields each year [35]. Traditionally, pest management has relied on manual field scouting, pheromone or sticky traps, and weather-based models to predict outbreaks. These methods are often slow and reactive, providing little lead time for preventive action. As a result, farmers frequently resort to blanket pesticide applications after infestations are already widespread, incurring high costs and environmental impact [17]. There is a growing consensus that agriculture needs more proactive, data-driven surveillance to stay ahead of pest populations. Modern technological advances are beginning to fill this gap [36, 76]. Unmanned Aerial Vehicles (drones) equipped with high-resolution cameras and sensors can rapidly scan entire fields and orchards from low altitudes. The imagery and data collected by drones are then analysed by artificial intelligence (AI) and machine learning algorithms. Computer vision techniques automatically identify insect pests and plant stress signatures in aerial images, while predictive models use weather and historical data to forecast how pest populations will evolve [23, 108]. By combining real-time sensing with AI-driven analytics, these systems can generate early-warning maps of pest hotspots and development [61]. Such tools effectively create automated decision-support systems for farmers. Targeted advisories and precision spraying become possible, meaning that only infested zones are treated and healthy areas are left untouched. This precision approach leads to reduced pesticide use, lower costs, and healthier crops [47].

This article examines the integration of drones and AI in insect surveillance and pest forecasting. First, we review the theoretical background: how remote sensing (from satellites and UAVs) works, the role of various sensors, and the basics of AI-based image recognition, alongside an overview of traditional pest control and forecasting methods [121, 62]. Next we describe technological advancements: how modern UAV platforms and smart imaging sensors work together with AI algorithms to detect pests, issue real-time alerts, and even automate control actions like targeted spraying. We then explore practical applications, highlighting case studies from India (such as the new National Pest Surveillance System) and around the world where AI-enabled drones have improved early detection and response. We discuss the benefits of this approach including increased yield, resource efficiency, and timeliness as well as the remaining challenges, from infrastructure and cost to policy and data issues. Finally, we outline future prospects, illustrating emerging trends (like drone swarms and edge AI) that promise to make pest management even more precise and predictive [7, 48].

Table 1: Types of Drones and Their Applications in Pest Surveillance

Drone Type	Key Features	Pest Surveillance Applications
Multi-Rotor (Quadcopter/ Hexacopter)	Vertical take off/landing, high maneuverability, stable hover, moderate range	Localized monitoring: precision imaging and spraying in small fields or orchards; indoor/greenhouse inspections. Enables close-up inspection of plants for pests or diseases.
Fixed-Wing	Long-range, high endurance, fast horizontal flight	Broad-area surveying: rapid mapping of large fields and landscapes. Used for large-scale field scans (e.g. cereal crops, plantations) and monitoring migrating pest swarms.
VTOL Hybrid	Vertical take off plus efficient cruise flight	Flexible deployment: Combines benefits of multi-rotor and fixed-wing. Can quickly launch and then cover wide area. Suitable for varied terrain, e.g. hilly farms.
Rotary-Wing Helicopter	High payload capacity, long endurance, vertical lift	Heavy-duty spraying: Lifts large tanks of pesticide/fertilizer for covering many acres. Also used for high-altitude surveillance or remote-area mapping with powerful sensors.
Nano/Micro Drone	Very small size, lightweight, ultra-precise flight	Close-quarters monitoring: Inspecting under foliage or between vines, indoors or under greenhouse benches. Ideal for detailed crop scouting or even pollination assistance.
Sprayer Drone (Agri-UAV)	Large chemical tank, multiple nozzles, precision controls	Targeted application: Carries pesticides or biocontrol agents to spray exactly on identified pest hotspots. Reduces chemical usage by treating only infested patches.
Multispectral Imaging UAV	Equipped with multispectral or hyperspectral camera	Spectral analysis: Captures plant reflectance at various wavelengths (visible and near-IR). Detects early stress or feeding damage invisible to RGB, enabling early pest alerts.
Thermal Imaging Drone	Mounted thermal infrared camera	Heat-stress detection: Identifies plant stress or insect colonies via heat anomalies. Useful for spotting whitefly aggregations or locating animals that vector pests.
LiDAR-Equipped Drone	Carries LiDAR scanner for 3D mapping	Structural mapping: Generates high-resolution 3D models of crop canopy. Helps detect canopy thinning or defoliation patterns caused by borers or beetles in forests and orchards.
Drone Swarm	Multiple coordinated drones, networked	Parallel scanning: Covers very large farms quickly. Each UAV covers a sub-area; swarm AI algorithms integrate data. Useful for time-sensitive outbreaks (e.g. locusts, armyworms).
Under-Canopy Drone	Small, agile frame designed for low flight	Sub-canopy inspection: Flies under tree canopies or between tall crops to inspect leaf undersides and fruit. Detects pests hidden from above, such as aphids or scale insects.
Tethered Drone	Stationary drone attached by cable (power/GPS)	Persistent monitoring: Remains airborne for long periods (hours/days) above traps or critical zones. Provides continuous imaging (e.g. around livestock or greenhouses) to catch pest activity in real time.
Solar-Powered HALE UAV	High-Altitude, Long-Endurance (solar/hydrogen)	Ultra-wide surveillance: Hovers at stratospheric altitudes for weeks. Monitors very large regions (e.g. crop belts) and relays data; potentially used for broad pest trend observations.
Greenhouse Monitoring UAV	Automated indoor drone or sensor rig	Controlled-environment scanning: Continuously surveys greenhouse plants for pests and diseases. Examples include camera-equipped drones that trigger insect traps or predator releases.
Predator-Interceptor UAV	Tiny autonomous drone (conceptual)	Pest interception: (Experimental) Drone programmed to seek and intercept flying insect pests (e.g. moths) in mid-air. Represents future biological control method with minimal chemical use.

Theoretical Background

Historically, farmers have combated insect pests through cultural controls (crop rotation, resistant varieties), chemical pesticides, and constant field monitoring. Integrated Pest Management (IPM) stresses careful surveillance of crops so that control measures (like pesticide sprays or biological controls) are used only when needed [109, 49]. Traditional surveillance methods include manual field scouting and stationary traps. For example, pheromone-baited traps or light traps count adult moths or flies, providing an indirect indicator of larval populations [78, 37]. Agronomists also visually inspect sample plots for signs of chewing, discoloration, or other damage. Simple weather-based "degree-day" models and historical outbreak records are used to roughly forecast key pest lifecycle events (such as egg hatch or migration). However, these conventional approaches are labour-intensive, time-consuming, and limited in scale [122, 8]. They can easily miss rapidly developing infestations until crops are visibly damaged, forcing delayed, often area-wide pesticide applications. Thus, traditional pest forecasting frequently results in over-application of inputs and avoidable yield losses. There is a clear need for more continuous, high-resolution monitoring to implement IPM effectively [24]. Remote sensing technologies have long been applied in agriculture to monitor vegetation at large scales [1]. Satellite imagery and manned aircraft can measure indices like NDVI (Normalized Difference Vegetation Index) that correlate with plant health, but these approaches often lack the spatial detail and revisit frequency needed for pest detection [64, 110]. Unmanned Aerial Vehicles (drones) overcome this gap by flying at low altitudes and capturing very high-resolution data. Modern agricultural drones come in different airframe types (multirotor, fixed-wing, hybrid VTOL, etc.) and can carry a variety of sensors [79, 111]. These may include high-resolution RGB cameras, multispectral or hyperspectral cameras (capturing specific wavelength bands beyond the visible), thermal infrared cameras, and even LiDAR units for 3D canopy mapping. Each sensor provides different clues [80]. For instance, healthy vegetation strongly reflects near-infrared light, so areas where pests have damaged leaves will stand out as anomalies in multispectral images. Thermal cameras can reveal subtle temperature differences, potentially indicating plant stress or large clusters of insects (e.g. a swarm might emit extra heat). As a drone flies, it collects geotagged data points or overlapping photographs, which can then be stitched into detailed maps of the field [50]. These maps reveal spatial patterns of plant stress or discoloration that may indicate pest activity long before human scouts notice it. Processing this wealth of data relies on AI techniques. In particular, machine learning models can be trained to recognize pest-specific signatures in images and sensor data [65]. Convolutional Neural Networks (CNNs) have revolutionized image recognition: given sufficient labelled examples, a CNN can learn to distinguish between healthy foliage and damage caused by a particular caterpillar or beetle species [123, 9]. Object-detection networks (like YOLO or Faster R-CNN) can even locate and count individual insects or eggs in an image [81]. Other models support vector machines, decision-tree ensembles (random forests or gradient boosting) can classify patterns in spectral or time-series data. Recurrent neural networks (LSTM, GRU) or other time-series models can analyze sequences of weather and trap-count data to forecast pest population trends [112]. In short, AI algorithms sift through multi-dimensional data to classify pests and predict outbreaks. By automating identification and trend analysis, they turn raw images and trap counts into actionable insights [66].

In addition to drone imagery, many surveillance systems integrate ground-based sensors. Smart traps equipped with cameras or acoustic microphones can detect and sometimes identify insects as they enter [18]. Soil and weather sensors (measuring moisture, temperature, humidity) feed the network with environmental context [113]. This Internet-of-Things (IoT) data is incorporated into predictive models. For example, a model might take recent trap counts, local temperature/precipitation data, and plant growth stage to issue an early warning of an impending infestation [124, 82]. The theoretical foundation of modern pest surveillance thus combines classical agricultural science (pest ecology, IPM principles) with cutting-edge sensing and AI: continuous data collection from drones and sensors is analyzed by intelligent algorithms to enable a proactive approach to crop protection [51].

Table 2: Key AI Techniques Used in Pest Identification and Forecasting

AI Technique	Description / Application
Convolutional Neural Networks (CNNs)	Deep learning models trained on images to classify insects or damage. Used to identify pest species from photos of leaves or traps.
Object Detection (YOLO, R-CNN)	Real-time detection models that locate and count pests within an image. Enables spotting individual insects (e.g. locusts, caterpillars) in drone photos.
Recurrent Neural Networks (RNN / LSTM)	Models that analyze temporal sequences. Used for forecasting pest populations or migration over time based on historical counts and weather data.
Support Vector Machines (SVM)	Classical ML classifiers. Employed to distinguish pest vs. non-pest image patches or sensor spectra when data is limited.
Random Forest / Gradient Boosting	Ensemble tree-based models for robust classification/regression. Used to predict outbreak risk from combined features (e.g. trap counts, climate data).
Bayesian Networks	Probabilistic models incorporating expert knowledge. Used for risk assessment, accounting for uncertainty in pest spread under varying conditions.
Transfer Learning	Adapting pretrained image models to new pest datasets. Allows rapid deployment of AI by fine-tuning general models (e.g. from common crops) to specific local pests.
Unsupervised Clustering (K-Means, DBSCAN)	Grouping data without labels. Helps detect unusual pest population patterns or group fields with similar infestation levels.
Ensemble Learning	Combining multiple AI models (bagging, boosting) to improve accuracy. For example, merging CNN and SVM predictions to reduce misclassification of pests.
Graph Neural Networks	Advanced models for spatial data. Can represent farm areas as connected nodes, learning how pest pressure in one part of a field influences neighbouring areas.
Autoencoders / Anomaly Detection	Neural nets that learn normal crop patterns and flag deviations. Useful for spotting novel pest outbreaks as anomalies in imaging or sensor data.
Semantic Segmentation	Pixel-level classification (e.g. U-Net). Used to outline diseased leaf areas or infested crop sections in aerial images.
Reinforcement Learning	Training AI agents (e.g. drone control policies) via trial and error. Could optimize flight paths or spraying strategies to maximize pest coverage with minimal resources.
Hyperspectral Analysis	Deep learning applied to hyperspectral cubes. Differentiates subtle biochemical changes in plants caused by specific pests, enabling early detection.
Data Augmentation / GANs	Techniques to synthetically expand training datasets. Generative Adversarial Networks (GANs) can create realistic pest images to train models, improving detection of rare pests.

Technological Advancements

Modern drone platforms act as the "eyes" of a precision pest management system. They are built with GPS navigation, autopilot capability, and pre-programmed flight paths, allowing a single UAV to systematically survey large farms multiple times per week. These drones can carry an array of sensors on a single flight [84]. For example, a drone might mount a high-resolution RGB camera for visual data, a multispectral imager for vegetation indices, a thermal camera for heat mapping, and even a lightweight LiDAR unit for 3D canopy structure [83]. As the drone flies over a field, it continuously collects geotagged imagery and sensor readings at centimeter-level resolution [26, 114]. This raw data is typically streamed wirelessly or downloaded after the flight and then fed into AI processing pipelines.

Once the data is collected, AI-driven software analyzes it to detect and forecast pests. Computer vision algorithms can stitch the drone's photographs into a large orthomosaic map, then apply convolutional neural networks (CNNs) to each image tile [39]. The CNN may be trained to recognize specific insects (for instance, spotting fall armyworm caterpillars or whitefly clusters on leaves) or damage patterns (such as holes, mines, or milky aphid secretion) [85]. Other algorithms compute plant stress indices from multispectral data (e.g. anomalies in near-infrared reflectance). By overlaying successive maps in time, the system can also identify new areas of deterioration [115]. Simultaneously, machine learning models may incorporate weather forecasts and historical data to predict how a detected pest population will spread [52]. Many platforms automate the entire workflow: the moment a drone survey detects a dangerous pest level in one corner of the farm, the system flags it on a map. Farmers then receive an alert through a smartphone app or dashboard, pinpointing exactly which fields or rows need attention [86]. In practice, these technologies form a closed-loop monitoring-and-response system. Drones fly on schedule, AI analyzes the imagery, and decisions are made automatically or semi-automatically [2]. For example, if a surveillance drone spots an outbreak of stem borers in a cotton field, the system can automatically dispatch a pesticide-spraying drone loaded with the appropriate insecticide, directed only to the affected sections [116]. This means that sensing and actuation occur in quick succession: the time from detection to intervention is drastically shortened [86]. In high-tech greenhouses, fully automated micro-drones or ceiling cameras now vigilantly watch for flying insect pests. In one demonstration setup, ceiling-mounted cameras identify harmful flies by wingbeat frequency and size; tiny bat-like drones are then released from charging stations to intercept and kill only those pests mid-flight, leaving beneficial insects untouched [87]. Such innovations illustrate the broad reach of drone-AI integration, from sprawling open fields to controlled-environment agriculture, making pest control both smarter and more efficient [117].

Networking and connectivity enhancements further boost these systems. As 5G and IoT infrastructure expand into rural areas, drones can stream high-definition video to cloud servers in real time for rapid analysis [10]. Multiple drones can work in concert: for instance, a leading UAV might transmit data to other drones in flight, enabling a coordinated “swarm” search of a large plantation. Cloud platforms can aggregate data from satellite imagery down to drone data to create a unified monitoring framework [88]. Over time, shared databases allow AI models to improve by learning from many farms and regions, covering diverse pest species and crops. In summary, the technological trend is toward fully integrated systems: autonomous drones gather data and, guided by AI, trigger precise responses, transforming pest forecasting into a fast, data-driven process rather than a slow manual task [40].

Applications in India and Globally

AI-enabled drone surveillance and analytics are being adopted worldwide, from smallholder farms to national programs. In India, for example, the government has launched several initiatives to leverage these technologies [89]. In 2024 the National Pest Surveillance System (NPSS) was rolled out under the Digital Agriculture Mission. This AI-driven platform allows farmers to upload images of diseased plants from over 60 major crops; the system uses image recognition to identify the pest or disease and immediately provides management advice through mobile and web apps in local languages [90]. The NPSS has already issued thousands of real-time advisories for crops like rice, wheat, maize, cotton, pulses, mango, and banana. States have also piloted AI-drone programs. In Maharashtra’s cotton belt, drones equipped with cameras and AI models scan fields for bollworm infestations, enabling precise spraying and significantly reducing damage [101]. The early success led the state to formalize an “AI in Agriculture” policy for 2025-2029. Private enterprises and farmers are also embracing drone-AI tools [27]. In Kerala and Karnataka, start-ups have introduced drone sprayers that cover several hectares in minutes; one company reported that cotton and rice farmers saw ~30-35% yield increases and slashed water and fertilizer use by over half after switching to precision spraying [53]. Horticultural farmers use sensor networks and smartphone apps to complement aerial monitoring. For instance, soil moisture and weather sensors installed by an agri-tech firm now serve tens of thousands of acres of orchards and fields, helping growers only water and fertilize when plants truly need it (healthier plants are more resistant to pests) [19]. In a mango orchard in Telangana, farmers simply photographed a diseased leaf with a mobile app. The app instantly diagnosed a fungal infection (sooty mold) and recommended a fungicide, preventing what could have become a costly outbreak [41, 100]. This kind of smartphone-based AI diagnosis (such as the Plantix app, which covers 30+ crops and multiple languages) empowers farmers to act on pest problems in real time, complementing drone observations [28].

Table 3: Comparative Pest Outbreak Cases: Traditional vs AI-Drone Forecasting Systems

Pest & Crop (Region/Year)	Traditional Forecasting & Response	AI + Drone Forecasting & Response
Fall Armyworm (Maize, Africa)	Manual trap surveys and field checks; often alerts arrive after larvae are widespread, causing heavy defoliation and yield loss.	Drones survey fields with multispectral cameras; AI spots stressed patches early and predicts spread; enables targeted spraying on infestation zones, greatly reducing damage.
Desert Locust (Africa/India)	Ground patrols and farmer reports; broad aerial pesticide spraying after swarms appear; often slow to react as swarms move quickly.	Drones equipped with thermal/multispectral sensors map swarm locations and breeding sites; AI forecasts swarm movement; allows pre-emptive, focused spraying, containing outbreaks faster.
Pink Bollworm (Cotton, India)	Pheromone trap counts; scheduled or reactive spraying; infestation often advanced before control, leading to cotton boll damage.	Aerial surveillance identifies moth concentrations or early larval damage; AI generates hotspot maps; precise insecticide or biocontrol release only where needed, protecting bolls.
Brown Planthopper (Rice, Asia)	Expert weather models (monsoon forecasts) and field scouting; routine insecticide programs; widespread spraying often used.	UAVs capture canopy images; AI detects subtle nutrient stress from hoppers; integrates weather data to forecast outbreaks; spot-treats or releases natural enemies at high-risk times, cutting blanket spray.
Colorado Potato Beetle (Potato, USA)	Field inspections and calendar sprays; beetle populations often high before detection, requiring large insecticide use.	Drone scans for beetle eggs/larvae on plants; AI counts and maps densities; only infested rows are sprayed or treated with predators, reducing pesticide use while keeping beetle pressure low.
Codling Moth (Apple, Global)	Pheromone traps alert when moths emerge; timed orchard sprays; many fruit still struck by larvae inside before detection.	Drones image orchard canopies; AI identifies initial fruit damage or moth hotspots; enables targeted application of bacillus or mating disruptors to infected trees, reducing wormy apples.
Grape Mealybug	Sticky and visual traps; spot sprays often only	Multispectral and RGB drone imagery highlight infested vines; AI locates

(Vineyard, USA/EU)	after mealybugs spread; virus transmission may occur before control.	mealybug colonies; treatments (parasitoid releases or spot sprays) are applied only to those vines, limiting spread.
Pine Bark Beetle (Forest, N. America)	Ground crews survey and mark red/browning trees; salvage logging after heavy infestations, with significant timber loss.	High-altitude UAVs use thermal and spectral sensors to detect infested trees by heat and reflectance; AI maps outbreak perimeter; enables early tree removal or pheromone trapping ahead of spread.
Whitefly (Vegetables, Global)	Calendar-based blanket sprays; little actual scouting; populations often resistant; environmental impact.	Periodic drone flights count whitefly on leaf images using AI; threshold alerts trigger targeted sprays or biocontrol release in affected crop patches, preserving beneficials elsewhere.
Mango Hopper (Mango, India)	Regular scheduled spraying; effectiveness varies; heavy pesticide use; often misses localized outbreaks.	Field drones and sticky traps feed image data to AI; it detects hopper hotspots on specific trees; enables spot application of bio-pesticides on infested trees, boosting yield and reducing chemicals.
Soybean Aphid (Soybean, USA)	Manual sampling against action thresholds; broad insecticide campaigns if thresholds exceeded; late timing common.	Weather and satellite data feed AI models that predict aphid flights; drones confirm early infestations; precise treatment or resistant variety planting is enacted before major damage.
European Corn Borer (Corn, Europe)	Pheromone traps and scouting; seasonal sprays or Bt maize; many maize ears still perforated by larvae.	Drones with hyperspectral imagers detect early feeding stress; AI forecasts second-generation hatch; targeted foliar sprays or localized Bt release protect vulnerable areas.
Cotton Bollworm (Cotton, Africa)	Often blanket pesticide applications (older organophosphates); high application frequency; resistant populations persist.	UAVs scout for bollworm egg pods; AI pinpoints infestation clusters; focused release of baculovirus or safe biopesticides only in hot zones, lowering chemical load while controlling the pest.
Sugarcane Stem Borer (India)	Soil drenches or uniform foliar sprays twice yearly; spotty coverage; labor intensive and costly.	Drone NDVI mapping reveals cane patches with dead hearts (infestation symptom); AI flags those areas; targeted application of entomopathogenic nematodes or endophytic treatments concentrates on problem spots.
Coffee Berry Borer (Coffee, Latin America)	Sweep nets and canopy fogging; many infested berries escape treatment; final yield and quality drop.	High-resolution drone imaging of coffee trees; AI identifies boreholes on berries or entrance sites; spot fumigation or release of parasitoids in flagged areas improves harvest quality.

Globally, similar success stories are emerging. In Africa and the Middle East, governments and NGOs have flown drones to combat locust swarms [102]. UAVs equipped with thermal and multispectral cameras can spot swarm aggregations and vegetation greening in deserts, guiding targeted aerial spraying of pesticides [20]. For example, UN-backed operations in Kenya and Somalia tested drones that quickly mapped potential locust breeding grounds, enabling focus on hot spots [11]. In the Americas, large farms use drones to survey crops for invasive pests; U.S. corn and soybean growers, for instance, employ drones with AI to detect fall armyworm and corn borer early in the season, allowing precise interventions [29]. In China, authorities have integrated thousands of agricultural drones into rice and cotton fields both for spraying and for imaging crop health; data analytics then predict pest outbreaks so that interventions can be timed [42]. In Europe and Australia, researchers and farmers likewise use drones for specialty crops: vineyards and orchards are scanned for grapevine moth, codling moth, and fruit fly infestations, often combining drone data with weather models to forecast hot spots [43]. Innovative products have even emerged: Dutch engineers have developed palm-sized indoor drones that fly among greenhouse tomatoes or peppers, intercepting moths in mid-air (killing them on contact) based on AI flight-pattern recognition, thus providing pesticide-free control [54]. In all these cases, integrating drones with AI transforms pest monitoring from sporadic field checks into continuous, data-rich surveillance, improving resilience in crop protection worldwide [3, 103].

Benefits and Impact

- **Early detection of pests:** By uncovering infestations at their onset, drone-AI systems allow intervention before the damage spreads. In practice, farmers report catching outbreaks weeks sooner than with manual scouting, preventing what could have become major yield losses [55].
- **Targeted treatments:** Precise maps of pest hotspots mean that pesticides or biological controls are applied only where needed. This drastically cuts chemical usage and cost. Studies and field reports indicate pesticide reductions of 30-70% when using precision UAV spraying versus blanket sprays [44, 104].
- **Increased yield and quality:** With pests held in check more effectively, overall crop productivity improves. Trials have shown 15-35% yield increases in fields managed with drone/AI surveillance, since plants suffer less damage. Produce quality is also higher (e.g. cleaner fruit) when infestation levels are minimized [31, 67].
- **Labor and time savings:** A single drone flight can cover dozens of acres in minutes, a task that would take a team of scouts many hours or days. This efficiency frees up labour for other tasks. In regions with labour shortages, automating field surveys is a major advantage [56].
- **Resource efficiency:** AI analysis often integrates other farm data (soil moisture, nutrient levels), so that overall farm management improves. For example, healthier (well-watered, well-nourished) plants are less susceptible to pests; drones identifying water-stressed areas help farmers irrigate optimally, thereby indirectly reducing pest risk. Resources like water and fertilizer are used more judiciously, improving sustainability [118, 12].
- **Environmental and safety benefits:** Reduced pesticide use means less chemical runoff into soil and waterways and lower exposure risk for farm workers and beneficial insects. Precision applications also allow use of targeted biocontrol agents (parasitoids, pheromones) instead of broad-spectrum poisons. Many projects highlight improvements in farmer health and ecosystem biodiversity when switching to precision methods [45].
- **Better decision-making:** The data collected build a historical record of pest activity. This knowledge enables more accurate forecasting and planning. Farmers can adjust planting dates, choose resistant varieties, or rotate crops more strategically. On a national scale, aggregated data can inform policy and insurance decisions [68].
- **Economic gains:** All of the above translate into better farm profitability. Higher yields and lower input costs improve net income. Some reports suggest return-on-investment times of just a few seasons after adopting drone/AI pest management [13, 32].

Table 4: Challenges and Mitigation Strategies for Drone and AI Adoption in Pest Surveillance

Challenge	Mitigation Strategy
High equipment and operational costs	Government subsidies, leasing/rental schemes, cooperative purchasing to lower entry barriers for small farmers.
Lack of technical expertise	Training programs and field schools for farmers; extension workshops; partnerships with agri-tech providers.
Poor rural connectivity	Use of edge computing on drones (offline AI analysis); investment in 5G/Internet infrastructure in farming zones.
UAV regulatory restrictions	Streamlined drone licensing and clear agri-UAV policies; creation of approved low-altitude zones for agriculture.
Data privacy and ownership concerns	Implementation of secure data standards; farmer-controlled data-sharing agreements; anonymized datasets.
Limited training data for AI models	Development of open-access pest image databases; crowdsourcing labels from farmers; international data collaborations.
Reliability and accuracy of AI	Rigorous validation and field testing of models; combine AI insights with agronomist review; use of explainable AI.
Weather and environmental constraints	Robust drone designs (waterproof, high-wind stability); alternative sensors (radars) in poor light; flight scheduling apps.
Battery life and endurance limits	Adoption of advanced battery tech; solar or fuel-cell UAVs; coordinating multiple flights to cover large areas.
Integration with existing farm systems	Adoption of open APIs and interoperability standards; modular platforms that can plug into farm management software.
Farmer adoption and trust	Demonstration projects and pilot programs showing clear benefits; user-friendly interfaces; local language support.
Maintenance and support infrastructure	Establishment of local UAV service centers; training farmers in basic drone maintenance; spare-part networks.
Environmental impact (wildlife, noise)	Guidelines for eco-friendly operations (quiet rotors, wildlife-safe altitudes); impact assessments before deployment.
Cybersecurity and data protection	Encrypted communications for drone data; secure firmware updates; authentication protocols to prevent unauthorized access.
Socio-economic inequality	Inclusive programs targeting smallholders (community-shared drones, subsidies); addressing affordability to avoid digital divide.

Limitations and Challenges

Despite their promise, drone-and-AI surveillance systems face several challenges. Infrastructure in many farming regions is limited: poor internet connectivity in rural areas can hinder real-time data transmission, and local power or charging stations may be scarce for maintaining drone operations [57]. The UAV hardware itself can be expensive, especially sophisticated models with advanced sensors, which can be a barrier for small-scale farmers [119]. Harsh weather is another factor; drones cannot fly in heavy rain or strong winds, and cloud cover can reduce the quality of optical and thermal images. Battery life and payload capacity also limit flight duration and sensor combinations, although these are improving [69].

Regulatory and operational issues also arise. Many countries have strict rules on drone flights (altitude limits, no-fly zones, licensing requirements), which can complicate regular agricultural use [105]. Standardizing protocols for safe drone use and finding insurance or liability solutions are ongoing concerns [14]. On the AI side, reliable pest identification depends on high-quality training data [33]. Diverse pest species and local variations mean models must be frequently updated; a model trained in one region may misidentify pests in another. Mistakes (false positives or negatives) can reduce farmers' trust in the system [58]. Interoperability is another hurdle: there are many manufacturers of drones, sensors, and AI platforms, but no universally adopted standards, making integration into existing farm management systems complex [4].

Social and economic factors also play a role. Farmers may be hesitant to adopt new technology without clear support and training. Extension services and government programs may need to ramp up education on how to use these tools effectively [34]. Data ownership and privacy concerns have emerged: farmers may worry about who can access the aerial data of their fields and how it might be used [70]. Finally, there are broader concerns to address: ensuring equitable access so that smallholder farmers can benefit (not just large commercial farms), and minimizing any negative impacts of UAVs on wildlife or farm communities. Overcoming these challenges will be key to unlocking the full potential of AI-driven pest surveillance [21].

Future Prospects

The future of pest surveillance looks increasingly autonomous and integrated. Drone technology continues to advance: newer UAVs promise longer flight times through solar or fuel-cell power, enabling continuous monitoring of large areas [59]. Miniaturization is advancing too, with micro-drones able to navigate complex canopy structures or greenhouse aisles. Swarm technology, where multiple drones coordinate a survey in parallel, is on the horizon such systems could map vast plantations in minutes [71]. Connectivity improvements, such as widespread 5G and IoT networks, will allow drones to transmit data instantly and coordinate with other farm machines in real time. Artificial intelligence is also evolving [15]. Next-generation models will be more adaptable, using transfer learning to apply knowledge from one region's pest problems to another's [106]. Federated learning and shared data platforms could allow models to improve collectively without exposing private farm data [120]. Edge computing (AI running directly on the drone) will become more common, giving immediate feedback even where internet is weak [72]. Researchers are exploring sophisticated algorithms like graph neural networks to model the spatial spread of pests across a landscape, or reinforcement learning to optimize drone flight paths and treatment strategies [107]. Generative AI might help too, by simulating pest population dynamics under climate change or by creating synthetic training images to improve rare pest detection [46]. Integration with other technologies will create even smarter systems. For example, data from satellites, weather stations, drones, and farmer smartphone reports could be fused into a "digital twin" model of a farm's ecosystem [73]. Augmented reality (AR) could allow agronomists to view pest maps overlaid on their tractor's windshield or on a tablet in the field. Blockchain and secure data-sharing protocols might enable traceable, farmer-controlled pest data exchanges [5]. On the hardware side, we may see hybrid drones that both monitor and act for instance, drones that release sterile insects or distribute pheromones in response to detected infestations [74]. Advances in robotics could see ground vehicles working in tandem with aerial drones (aerial scans identify weeds or pests, then an autonomous tractor steps in to target-spray) [22]. Regulatory and support systems are likely to adapt as well: we can expect clearer UAV guidelines for agriculture and more government incentives for precision farming tech. Education and extension services will continue to help farmers adopt AI tools [75]. In the longer term, the vision is of a fully connected, sensor-driven farming system where pests are anticipated and neutralized before they become a problem. Such a future will greatly enhance crop resilience in the face of new pest pressures and climate volatility [16, 60].

Conclusion

Insect pests will remain a major challenge for agriculture, but the convergence of drone technology and artificial intelligence offers powerful new tools to meet this challenge. By enabling continuous, large-scale surveillance with automated analysis, these systems shift pest management from reactive to proactive. Farmers gain earlier warnings of outbreaks, allowing for targeted treatments that save yield and reduce chemical usage. Case studies from India and around the world demonstrate clear benefits higher productivity, cost savings, and more sustainable farming practices. However, realizing this potential will require investment in infrastructure, data, and training, as well as sensible regulation and support from governments and industry. With these challenges addressed, the integration of drones and AI is poised to reshape pest forecasting systems. The result will be more resilient crop production and enhanced food security as agriculture adapts to evolving pest threats and a changing climate.

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