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Review

The Role of AI-Integrated Drone Systems in Agricultural Productivity and Sustainable Pest Management

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Abstract

Artificial intelligence (AI)-assisted drone technology in agriculture has transformed productivity and pest control techniques, resulting in novel solutions to modern farming challenges. Drones utilizing sensors, cameras, and AI algorithms can precisely monitor crop health, soil conditions, and insect infestations. Using AI-assisted drones for precision irrigation and yield predictions further improves resource allocation, promotes sustainability, and reduces operating costs. This review examines recent advancements in AI and unmanned aerial vehicles (UAVs) in precision agriculture. Key trends include AI-driven crop disease detection, UAV-enabled multispectral imaging, precision pest management, smart tractors, variable-rate fertilization, and integration with IoT-based decision support systems. This study synthesizes current research to identify technological progress, implementation challenges, scalability barriers, and opportunities for sustainable agricultural transformation. This review of peer-reviewed studies published between 2013 and 2025 uses major scientific databases and predefined inclusion and exclusion criteria covering crop monitoring, precision input application, integrated pest management (IPM), and livestock (especially cattle) monitoring. We describe the platform and payload trade-offs that govern coverage, endurance, and spray quality; the dominant analytics trends, from classical machine learning to deep learning and embedded/edge inference; and the emerging shift from monitoring-only UAV use toward closed-loop decision-making (detection–prediction–intervention). Across the literature, the strongest opportunities lie in robust field validation, multi-modal data fusion (UAV + ground sensors + farm records), and interoperable standards that enable actionable IPM decisions. Key gaps include limited cross-site generalization, scarce reporting of economic indicators (ROI, payback period, and adoption rate), and regulatory and safety barriers for routine autonomous operations. Finally, we present some case studies to emphasize the feasibility and highlight future research directions of AI-assisted drone technology. Through this review, we aim to demonstrate technological advancements, challenges, and future opportunities in AI-assisted drone applications, ultimately advocating for more sustainable and cost-effective farming practices.

Keywords: artificial intelligence; UAV; precision agriculture; remote sensing; cattle monitoring; livestock management; pest control

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1. Introduction

Recent advances in lightweight sensors, low-cost UAV platforms, and machine learning have made aerial data collection and on-farm automation accessible to a much wider range of agricultural systems. UAVs are used for rapid field scouting and mapping, and increasingly for active interventions, such as precision spraying and targeted release of biological control agents. However, a critical gap persists between technical demonstrations and repeatable, economically viable deployment. Field performance can degrade due to weather and illumination shifts; occlusion and mixed symptoms; and differences across crop types, growth stages, and management practices. In addition, many studies report accuracy metrics without reporting the downstream decision value, such as reduced pesticide use, yield preservation, labor savings, or practical constraints (battery life, payload limits, connectivity, and regulation).

1.1. Background and Motivation

Agriculture remains the fundamental source of global food production, supplying essential staple crops such as wheat, rice, maize, and legumes. To sustain productivity, modern farming systems need sophisticated management techniques like integrated pest control, soil monitoring, and climate forecasting. Crop diseases, weeds, and insect infestations, however, still pose a serious threat to agricultural productivity and global food security as well as sustainable development [1]. Production pest-related losses could be comparable to the quantity of food required to feed over one billion people [2]. Several emerging technologies have been introduced to address these challenges, though they are not yet fully refined or globally adopted. One of the most promising innovations in this field is drone technology. These UAVs can perform tasks, such as aerial mapping, targeted pesticide spraying, and remote sensing of crop health, that were previously labor-intensive or impractical. Moreover, AI can further assist drone technology by detecting crop disease and pest damage, allowing for timely and targeted interventions. Drones equipped with high-resolution cameras and multidimensional or hyperspectral sensors allow users to monitor crop health and analyze agricultural growth phases with high accuracy and efficiency.

Drones assist farmers in making precise decisions about irrigation timing, fertilization, and insect management, which leads to enhanced crop quality and productivity. Crop monitoring enables farmers to track the health and growth of their crops in real time, allowing them to better manage resources, such as pesticides, fertilizer, and water [3]. By integrating AI-assisted drones into agricultural processes, farmers benefit from increased efficiency, reduced costs, and improved crop yield, making drone technology a pivotal solution in the future of modern agriculture. Table 1 positions this survey within the existing drone-based agricultural research by showing both shared and unique areas of focus. All prior surveys and our work address crop management, confirming it as a mature application domain, whereas livestock monitoring is only explicitly considered by Barbedo et al. [4] and this survey, and precision irrigation and yield prediction appear exclusively in this survey, highlighting its novel emphasis on resource optimization and productivity modeling. In the IPM domain, early infestation detection is consistently covered by Filho et al. [5], Saha et al. [6], and this survey, but precise pesticide application and the explicit goal of reducing chemical usage and environmental impact are discussed only by Filho et al. [5] and this survey, indicating that our review offers a more integrated perspective on both monitoring and environmentally conscious control. Furthermore, concepts related to livestock management, such as real-time tracking, health monitoring, and overall farm efficiency enhancement, along with the dual-function drone-based framework for multi-purpose integration, are unique to this survey, underscoring our contribution in unifying crop, pest, and livestock applications under a single conceptual framework. Finally, while all surveys, including ours, address core enabling technologies, such as AI and machine learning algorithms and sensor/camera systems, only a subset and this survey) systematically discuss adoption barriers and future opportunities, reinforcing the forward-looking and comprehensive nature of our review.

Table 1. Summary of core approaches and concepts in drone-based agricultural research.

Approach	Concept	Filho et al. [5]	Saha et al. [6]	Barbedo et al. [4]	Hafeez et al. [7]	This Review
Drone-Enabled Precision Agriculture	Crop management	✔	✔		✔	✔
	Livestock (cattle) monitoring			✔		✔
	Precision irrigation & yield prediction					✔
IPM	Early infestation detection	✔	✔			✔
	Precise pesticide application	✔				✔
	Reduction in chemical usage and environmental impact	✔				✔
Livestock (Cattle) Monitoring & Management	Real-time tracking					✔
	Health monitoring					✔
	Overall farm efficiency enhancement					✔
Dual-Function Drone-Based Framework	Multi-purpose drone integration					✔
Technological Advancements & Challenges	AI & machine learning algorithms		✔	✔	✔	✔
	Sensor & camera technologies	✔	✔	✔	✔	✔
	Adoption barriers & future opportunities	✔		✔		✔

Overall, the authors have searched and integrated all of these approaches into their work to provide a unified and holistic perspective on drone-based smart farming. In preparing this survey, the authors searched multiple academic databases, such as IEEE Xplore, Scopus, Web of Science, and Google Scholar, and then selected and compared representative studies from each source.

1.2. Assesssment with Existing Reviews and Contributons

In evaluating previous studies on livestock and crop management, a recurring theme is the significant economic loss associated with diseases, such as Foot and Mouth Disease (FMD) and mastitis. Numerous works [8] documented the impact of FMD on milk production and the potential need for culling, leading to substantial farm-level economic effects. Similarly, several works [9] demonstrated that mastitis in dairy cattle incurs both direct costs (veterinary care) and indirect costs (reduced milk yields). Additionally, the Food and Agriculture Organization (FAO) reported that low- and middle-income nations collectively lose billions of dollars annually to such diseases, exacerbating the vulnerability of these regions. Beyond disease management, natural disasters also pose a formidable threat by causing widespread damage to livestock and crops, reflecting a significant proportion of agricultural GDP losses in susceptible areas.

Table 2 presents a comparative overview of recent research on AI- and drone-based applications in agriculture, along with the contributions of the current paper. It organizes the works by author and year and then summarizes each study's main objectives and the key strengths highlighted by the authors. Regarding objectives, Andrew et al. [10]. focus on autonomous aerial biometric cattle identification in real farming conditions, including online target detection algorithms and drone hardware capable of onboard deep inference. Ali et al. [11] emphasize reviewing multi-sensor remote sensing technologies such as hyperspectral, LiDAR, and radar for crop yield prediction. Rajagopal et al. [12] investigate using drones, AI, and edge computing for early crop disease detection, precision pesticide application, and accurate classification of anthracnose in cashew leaves. Sharma et al. [3] examine integrating AI and IoT in precision agriculture, using case studies to show impacts on crop management. While several review papers emphasize one aspect of agriculture, such as livestock health or pest control, many fall short of providing an integrated approach that encompasses crop protection and animal farming [13]. Some reviews excel at detailing the technological underpinnings of drone-based imaging, yet overlook the socioeconomic and environmental factors affecting their adoption. Others offer extensive discussions on AI-driven disease modeling but fail to address the practical implementation challenges in diverse field conditions. By contrast, this review adopts a holistic perspective, combining the technical innovations of drone technology, the data-driven insights of AI-based disease and livestock monitoring, and the environmental considerations necessary for sustainable farming. In doing so, it offers a clearer path toward reducing labor intensity, lowering health risks associated with pesticide use, and ultimately maximizing agricultural productivity. This integrated viewpoint distinguishes the present work from the existing literature, as it not only identifies and evaluates emerging technologies but also proposes a cohesive framework for addressing the complex demands of modern agriculture. This comprehensive review aims to address several key challenges in contemporary agriculture by examining the existing literature on drone-assisted farming technologies and identifying gaps that can be bridged through innovative AI-driven solutions.

This paper can be logically described as a narrative review because its primary goal is to summarize and interpret existing research on drone-based smart farming rather than to perform a rigid, protocol-driven synthesis, such as a systematic review or meta-analysis. The authors identify key themes (precision agriculture, IPM, livestock monitoring, dual-function frameworks, and technological challenges) and then qualitatively compare representative studies within each theme, discussing similarities, differences, and gaps instead of applying statistical pooling or formal risk-of-bias tools. Moreover, the literature search focused mainly on the most recent five years, capturing current trends and technological advances and selectively including influential earlier works where needed to provide context, which aligns with narrative reviews that emphasize up-to-date, thematically organized discussion over exhaustive coverage of all historical studies. Specifically, this paper makes the following primary contributions.

(1) This study provides a thorough overview of state-of-the-art drone technologies in agriculture, emphasizing their potential and identifying significant drawbacks that prevent widespread use. (2) To improve overall herd management and animal welfare while saving time and labor expenses, this study suggests an AI-assisted framework for tracking and observing livestock (such as cows and goats). (3) This review describes an integrated pest management (IPM) approach that uses drones with sensors and AI algorithms for early pest detection and targeted insect eradication, thereby reducing the need for chemicals and the health hazards they pose to farmers and consumers. (4) To increase crop yield, reduce environmental effects, and advance sustainability, this overview summarizes the various

agricultural technologies currently accessible, ranging from automated data analytics to remote sensing, promoting sustainability.

Table 2. Comparison study with recent survey papers.

Authors & Year	Objectives	Strength of the Paper
Andrew et al. 2019 [10]	• Autonomous aerial biometric cattle identification in a real-world agricultural setting. • Algorithms performing online target detection, identification, and exploratory agency. • UAV hardware setup capable of deep inference onboard the flight platform itself.	Autonomous UAV-based biometric identification for agriculture using onboard deep inference and novel algorithms.
Ali et al. 2022 [11]	• Review of multi-sensor remote sensing (hyperspectral, LiDAR, radar) for crop yield prediction.	Overview of multi-sensor integration to improve prediction accuracy and decision-making in farming.
Rajagopal et al. 2024 [12]	• Use UAVs and AI for early identification of crop diseases and precision pesticide application. • Implement edge computing for instant disease analysis and intervention. • AI model to classify anthracnose in cashew leaves with high accuracy.	Early identification and instant disease analysis to classify anthracnose in cashew leaves.
Sharma et al. 2024 [3]	• Integration of AI and IoT in precision agriculture. • Showcases case studies to highlight their impact on crop management.	AI and IoT in precision agriculture, high-throughput phenotyping, and AgroBots for improved crop management.
This review	• Highlighting and identifying the major challenges affecting modern agricultural practices. • Early pest detection with minimal chemicals, ensuring farmer and consumer safety. • Keeping track of livestock, and improving herd management and animal well-beings. • Agricultural technologies boost yields, sustainability, and eco-friendly farming.	AI-assisted drones for agriculture, optimizing pest control, livestock monitoring, and precision farming for efficiency and sustainability.

1.3. Identified Research Gaps and Open Challenges

Although the research has been advancing very fast, there are still a number of gaps that have not been addressed. To start with, most AI-based pest and disease detection models are trained on single-curated datasets that are recorded in controlled settings, and it is not clear how they can perform in the field where illumination, crop density, and weather conditions are irregular. Second, the ability to discriminate between visual similarity of stressors, including nutrient shortage, bacterial infection, and pest damage, is one of the greatest problems of UAV-only systems, especially in the initial stages of growth. Third, tiny and canopy-concealed pests (e.g., brown planthopper in rice) cannot be detected using aerial imagery alone and so there is a need to have a hybrid workflow that combines UAVs with ground sensors or close-range imaging. Fourth, the vast majority of studies are focused on technical accuracy without focusing on the long-term field validation, scalability, and economic sustainability. Lastly, the focus on regulatory constraints, data privacy, and usability by the farmers has not been a major point, which also has a significant impact on the actual adoption. Table 3 gives empirical evidence related to the identified research gaps.

Table 3. Empirical evidence related to the identified research gaps.

Aspect/Condition	Reported Effect on Performance or Sampling	Metric	Quantitative Value (As Reported)
UAV disease detection in field imagery [14]	Hybrid deep learning framework for wheat diseases using UAV imagery achieves high but variable performance across diseases in real-field images.	Accuracy, precision, recall, F1-score	Overall accuracy 74–97%; precision 73–96%; recall 73–95.7%; best variant reaches 97% accuracy and 96% F1
Height relative to canopy (occlusion) [15]	Drone net "grazing" the canopy captures significantly more insects than flying 1 m above, showing strong impact of canopy proximity/occlusion.	Insect yield (counts)	167 insects collected; height effect significant with $t = 4.9$, $p = 0.0017$; canopy-grazing (0 m) yields more insects than 1 m
Hyperspectral UAV system for crop health [16]	Drone-based hyperspectral imaging system for oil palm allows differentiation of health levels and supports disease detection and nutrient status.	Ability to separate health classes	Initial results show hyperspectral data are suitable to be used for differentiation of the healthiness level of oil palm stands
General environmental variability (light, canopy, background) [17]	Review notes that light variability, canopy complexity, and background noise degrade robustness of UAV deep learning models for pests/diseases.	Model robustness/error (narrative)	Environmental noise and complex backgrounds are explicitly cited as major challenges that "adversely affect" model performance

Motivated by these gaps, this review (1) synthesizes and compares state-of-the-art drone-based approaches for crop and cattle monitoring under realistic field conditions, (2) highlights quantitative findings related to environmental factors such as lighting and canopy occlusion when available, and (3) identifies how current methods fall short of delivering robust, scalable, and sustainable AI-assisted drone solutions for precision agriculture and livestock management.

1.4. Organization

This paper is organized as follows: Section 2 explores modern technologies in agriculture, including drone applications in livestock monitoring and precision farming. Section 3 discusses the design and development of agricultural drones. Section 4 focuses on integrated pest management using drones. Section 5 highlights various drone applications and Section 6 presents case studies, Section 6.5 outlines future directions, and Section 7 concludes this review.

2. Modern Technology in Agriculture

Modern crop production began with early techniques like manual irrigation and seed sowing. Basic irrigation systems, crop rotation plans, and better breeding practices have all contributed significantly to rising crop productivity over time. The introduction of mechanized agricultural equipment during the British Agricultural Revolution in the

18th century marked a significant turning point and greatly increased labor efficiency and productivity [18]. The development of agricultural technology has moved from basic tools to advanced equipment such as tractors, reapers, and mechanized shovels, significantly altering farming practices. By incorporating cutting-edge technologies like drones, smart tractors, AI-based monitoring systems, and precision pest and fertilizer management systems, agriculture has embraced digital transformation in recent decades. These tools not only improve efficiency but also support sustainable and data-driven farming practices.

2.1. UAVs in Agriculture

UAVs, often known as drones, have become pivotal instruments in the area of precision agriculture. The capacity to conduct aerial imaging allows farmers to oversee extensive fields effectively, evaluate crop health, prepare for irrigation, and identify pest issues. Utilizing multispectral and thermal sensors, drones are capable of detecting early indicators of plant stress, nutrient shortages, and disease occurrences, enabling swift action [19]. In addition to monitoring crops, drones are essential for managing livestock effectively. They assist in identifying grazing areas, monitoring animal movements, spotting irregularities in behavior or health, and offering immediate surveillance [20]. Figure 1 shows various functions that drones serve in the oversight and administration of livestock. Previous methods for monitoring livestock were predominantly based on the manual analysis of video captured by drones [21]. Nonetheless, recent developments have integrated thermal imaging [22], thresholding algorithms [19], and sliding window techniques [21] to enhance detection precision.

Figure 1. Different aspects of livestock management using UAVs.

Furthermore, AI-enhanced drones are capable of automating fertilizer and pesticide application with high precision, reducing input waste and environmental impact. The shift toward real-time, data-driven decision-making in agriculture is greatly supported by drone technology, which offers scalable and actionable insights into field conditions and animal welfare.

To maximize agricultural operations, precision farming, sometimes called precision agriculture (PA), uses comprehensive site-specific data. Various tools and techniques are included in precision agriculture, which aims to improve farming operations' accuracy and control [18]. These include sophisticated methods for crop monitoring and management, as well as self-sufficient equipment for planting and harvesting [19]. Real-time data on soil conditions, crop health, and weather patterns can be gathered by robotic devices outfitted with sensors, cameras, and other cutting-edge technologies. Precision agriculture saves resources, decreases environmental impact, and increases agricultural profitability by spraying pesticides where required. Figure 2 illustrates the concept of precision farming using drone technology. The future of precision farming is likely to be shaped by the continued evolution and integration of drone technology, with a focus on sustainability and meeting the increasing global food demand [22].

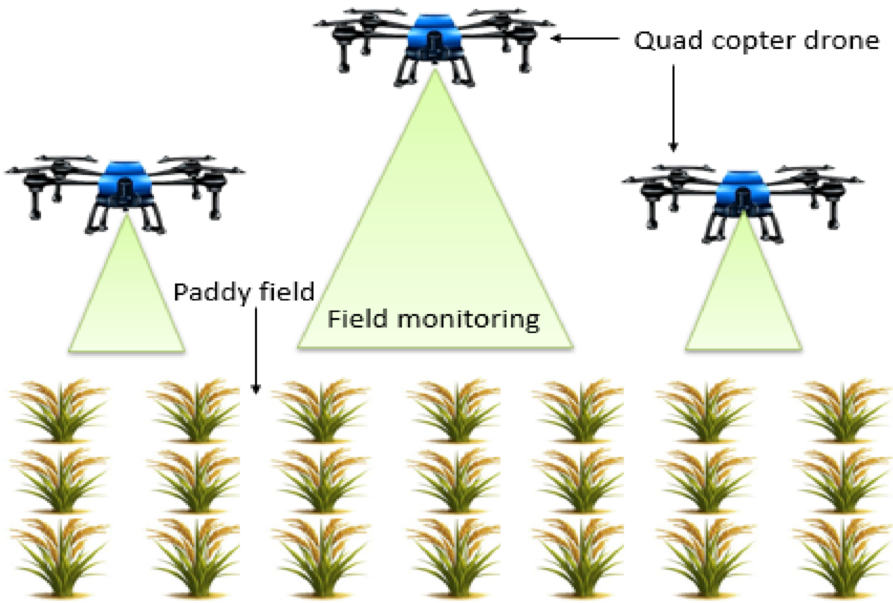

Figure 2. Illustration of precision farming using drone technology.

2.2. Smart Tractors and Autonomous Machinery

Autonomous or semi-autonomous vehicles with machine vision, AI, IoT, and GPS are known as smart tractors. These sophisticated machines are capable of executing various agricultural tasks like seeding, harvesting, and plowing, with limited human involvement, improving both accuracy and operational effectiveness. They employ sensor data to examine soil characteristics, enhance fuel efficiency, and modify operations in real time according to field conditions. Certain systems incorporate weather forecasts alongside historical yield data to strategically plan tasks in an adaptive manner. Information regarding crop performance, fuel efficiency, and soil conditions is gathered and transmitted wirelessly to farm management platforms for centralized decision-making and analysis. Instances encompass John Deere's fully autonomous tractor [23], integrating AI with GPS for hands-free fieldwork and remote monitoring through a smartphone app, alongside Kubota's Smart Agriculture System (KSAS) [24], which allows farmers to align machine operations with real-time data analytics and cloud-based task scheduling. These innovations greatly lower labor expenses, enhance productivity, and play a crucial role in the progress of data-informed sustainable agriculture. Farmonaut's technology is substituting conventional methods, increasing agricultural efficiency. It applies AI-powered yield prediction (85% more efficient, 65% cost savings), AI-driven irrigation management (70% more efficient, 50% cost savings), early satellite detection for pests and diseases (75% more efficient, 55% cost savings), and satellite-based imaging for crop health monitoring (80% more efficient, 60% cost savings). These developments reduce expenses and boost efficiency [25].

2.3. Blockchain for Traceability in Smart Agriculture

Blockchain technology is gaining acceptance in agricultural supply chains, promoting transparency, traceability, and trust among stakeholders. This system enables farmers, distributors, retailers, and consumers to securely log and access real-time information about each phase of a product's journey, from farm to fork. Agricultural producers can document details regarding the stages of crop development, the application of pesticides and fertilizers, the timing of harvests, the conditions of storage, and the logistics of transportation. Once data is incorporated into the blockchain, it achieves a state of permanence and can be verified, which reduces the risk of fraud, improves food safety, and guarantees equitable pricing.

Recent advancements feature the combination of blockchain technology with IoT devices, enabling automatic data gathering from sensors located in fields, greenhouses, or trucks. For example, sensors that monitor temperature and humidity in storage units can activate alerts and promptly refresh records on the blockchain when conditions surpass safe thresholds. Furthermore, blockchain technology is currently utilized to facilitate smart contracts, allowing for automatic payments to farmers upon confirmation of delivery conditions, thereby minimizing delays and dependence on intermediaries. Leading agricultural and retail firms, including IBM Food Trust, utilized by Walmart and Nestlé [26], are adopting blockchain technologies to enhance product traceability and bolster consumer trust. In developing nations, blockchain platforms facilitate microloans and crop insurance through the utilization of verified on-chain data, thereby minimizing financial risks for smallholder farmers.

2.4. Planning and Spraying by Drones

Aerial remote sensing is one of the crucial technologies for PA and smart farming. Drones are used in aerial remote sensing, which uses images to identify various crop conditions [27]. Crop remote sensing has changed because of improvements in drone technology and the weight reduction in payload devices. This method saves time, is less costly, and produces high-resolution photos without causing any damage to vegetation [28]. To design a drone for spraying applications, the first step is to determine the payload. Then, the components of the drone are selected after calculating the payload. The battery selection depends on the current and voltage requirements of the drone modules. Finally, the drone frame is designed depending on the number of arms and payloads. Both drones flying controllers and spraying systems have seen significant advancements in recent years. The semi-controlled spraying system has been replaced with a completely automated AI-based system.

In precision agriculture, pesticide spraying and crop monitoring are two tasks that require an aerial image processing system. Image processing efficiency depends upon aerial platforms, machine learning algorithms, and image-capturing systems. Figure 3 illustrates the block diagram of a fully automatic pesticide spraying system using drones. Drones have transformed crop spraying in modern agriculture using various techniques that improve environmental sustainability, precision, and efficiency.

The efficiency of drone-based agriculture spraying is influenced by a variety of factors, such as the size of droplets [29], flight altitude and speed [30], wind conditions [31], and the type of nozzle [32] applied. While coarse droplets reduce drift, they offer less coverage. In contrast, fine droplets increase coverage but are more susceptible to drift. In windy environments, drift can be mitigated through methods such as electrostatic spraying. The selection of a nozzle is essential for the specific crop types and field conditions.

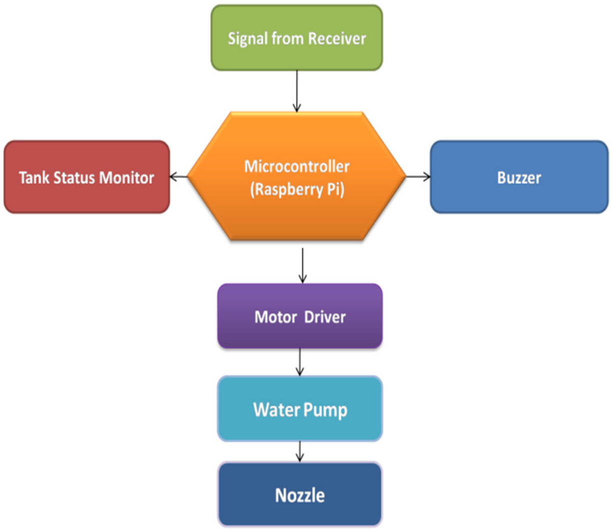

Figure 3. Block diagram of a fully automatic pesticide spraying system.

Figure 4 illustrates some key factors influencing spray efficiency in agricultural drone applications. Table 4 provides a helpful resource for understanding the different features and trade-offs offered by modern spray technologies when paired with agricultural drones. It highlights the significance of factors such as crop type, target pest or disease, desired level of precision, and operational scale when selecting a spraying technique. Some systems offer broad, cost-effective coverage, while others encourage better plant adherence, chemical conservation, and customized application, often at the price of complexity or early investment. This comparison research is essential for optimizing drone-based agricultural interventions, enabling more cost-effective resource usage, and enabling environmentally friendly pest and nutrient control methods.

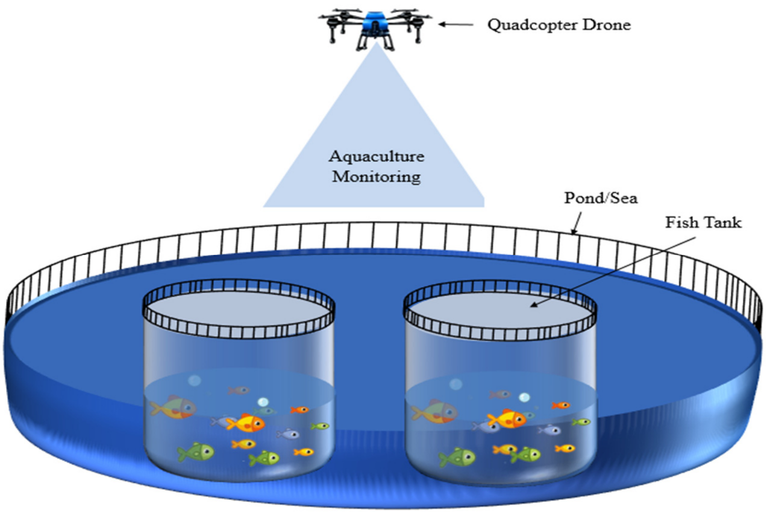

Figure 4. The traditional drone system for aquaculture monitoring and management.

Table 4. Agricultural drone spraying technologies with key parameters.

Spray Techniques	How It Works	Recommended for	Advantages	Limitations
Fixed Spray Nozzles [33]	Hydraulic nozzles release uniform spray	Broad-acre crops (wheat, rice)	Simple, cost-effective, wide coverage	Higher drift, less precise
Variable Rate Spraying (VRS) [34]	Adjusts spray volume via sensors/AI	Spot treatment (weeds, disease)	Saves chemicals, targeted application	Requires advanced sensors
Rotary Atomizer [35]	Spinning discs create fine droplets	Orchards, dense crops	Reduced drift, better adhesion	Higher power consumption
Electrostatic Spraying [36]	Charged droplets cling to plants	Cotton, fruit trees	Minimal waste, superior coverage	Complex setup, costlier
Ultrasonic Spraying [37]	High-frequency vibrations make mist	Fungicides, micronutrients	Ultra-fine droplets, even coating	Limited to low-viscosity liquids
Pulsed Spraying [38]	Intermittent spray bursts	Targeted weed control	Saves chemicals, reduces runoff	Requires precise timing
Aerial Boom Spraying [39]	Extended arms spray wide swaths	Large-scale farms	High efficiency, fast coverage	Bulky, less maneuverable

2.5. Monitoring Offshore Fish Farms

Food security and cost are two of the most pressing concerns for the world's growing population. Increasing food production while cutting costs and enhancing public access to food is challenging. Alternatively, many rely on fisheries for sustenance, particularly aquaculture and fish farming. Fish farming was a small-scale enterprise that supported a family or small group. Small-scale farmers were forced to enhance their farming techniques to boost production because of the growing need for aquaculture industrialization. However, theft and human attacks endanger aquaculture property security and can impact farm operations and profitability, particularly at large aquaculture sites with more financial resources and investments.

Moreover, human observation is difficult as a continuous, accurate, and consistent source of information due to its subjectivity and mistakes [29,36]. Numerous technological advances are applied to enhance aquaculture management and productivity. Expensive sensors are used by many to collect data. Additionally, the installation of several cameras is necessary for site-wide surveillance of the entire aquaculture area. Others employ costly drones with sensors, aerial cameras, and onboard computing power for site monitoring. Although they have a restricted power source, drones are dependable for surveillance. The drone's real-time operations are impacted by its computer power, which restricts its mobility, efficiency, and navigation time [30,40]. The traditional drone system for aqua monitoring and management is shown in Figure 4.

2.6. AI and Imaging Technologies for Pest and Disease Detection

Diseases and pests can be identified from images taken by drones, smartphones, or ground sensors using machine learning and deep learning algorithms. These technologies facilitate timely identification and proactive measures, minimizing crop losses and enhancing yield quality. Applications such as FarmWise [41] and PlantVillage Nuru [42] leverage computer vision technology to identify issues related to plant health and offer customized treatment recommendations, empowering farmers to make informed decisions based on data.

In an effort to reduce pesticide application and reduce environmental effects, automated robots are being engineered for targeted treatments and mechanical weed elimination. These systems leverage advanced technology to accurately identify the specific location and severity of infestation, facilitating precise intervention. This method effectively reduces the use of chemical inputs while protecting non-target organisms and promoting sustainable agricultural practices. With the increasing accessibility and affordability of these AI-driven systems, a notable rise in their adoption across farms of various sizes is anticipated.

The high expense of high-resolution satellite imagery, especially hyperspectral imagery, has typically restricted the use of these pictures to evaluate crop healthiness and production [43]. Drones offer a key advantage over space-borne sensors by providing high-resolution imagery at a lower cost and with flexible revisit schedules tailored to the user's needs [41]. Equipped with high-resolution cameras and multispectral or hyperspectral sensors, drones enable precise monitoring of crop health, early detection of diseases, and detailed analysis of growth stages. This level of granularity not only improves decision-making in agriculture but also contributes to resource efficiency and sustainable farming practices. These flying platforms can collect precise photographs of fields, enabling early diagnosis of pests, nutritional deficits, and irrigation problems. Drones help farmers make informed decisions about fertilization, pest management, and irrigation scheduling by giving real-time data on agricultural conditions, resulting in increased crop output and quality. Crop monitoring and management are important because they allow farmers to monitor the health and growth of their crops in real time, allowing them to better manage resources, such as water, fertilizer, and pesticides. Farmers may save money and reduce waste by targeting inputs precisely where they are most needed.

3. Design and Development of Drones for Agriculture Applications

To develop a dynamic unmanned aerial vehicle for agriculture applications, several intricate electronic gadgets need to be considered. Brushless DC motor (SunnySky/T-Motor, Nanchang, China), KK2.1.5 multi-rotor board, ESC (electronic speed controller), digital servo motor, and other electrical components are used in the implementation. The battery is constructed of lithium polymers. This section will cover all electronic components to design a drone for agricultural applications. Also, the creation of a telemetry system for real-time drone communication is presented. The following part describes the components and electronic parts needed to design a drone for use in agriculture.

3.1. Integration of Sensors and Software

For accurate navigation, a u-Blox NEO-M8N GPS module (u-blox AG, Thalwil, Switzerland) is integrated with the APM 2.8 Flight Controller (3D Robotics Inc., Berkeley, CA, USA), one of the essential parts. Furthermore, the inclusion of a dedicated power module ensures a clean power supply from a LiPo battery, monitors current consumption, and tracks battery voltage, thereby preserving both stability and reliability across a wide range of Drone operations. The drone consists of numerous sensors, telemetry modules, and power management components like the Pixhawk Power Module (3D Robotics Inc., Berkeley, CA, USA) and APM Shock Vibration Absorber to guarantee steady operation and accurate data recording. Additional essential components include a 600 mW video transmitter with a CMOS camera for high-quality imaging [44], a MinimOSD (3D Robotics Inc., Berkeley, CA, USA) for real-time telemetry overlay [45], and a Skydroid FPV receiver (Skydroid Technology Co., Ltd., Shenzhen, China) for video transmission. A GPS folding stand and a PCB board for sensor integration also improve data collection and signal reception. These technologies make it possible to monitor agricultural fields precisely and efficiently, which enhances tasks like resource management, pest detection, and crop health analysis.

3.2. Sustainable, Energy-Efficient Charging Station for Drones

Wireless charging technology for drones is a potential breakthrough that solves the shortcomings of existing cable charging techniques. Wireless charging provides convenience, efficiency, and improved operating capabilities to drone users in a variety of sectors by eliminating the need for physical connections. Wireless charging works by transferring electricity from a charging pad or station to the drone's battery without the need for direct touch. This technology allows drones to recharge their batteries automatically when they are stationed on approved charging pads or near charging stations, removing the need for manual intervention in typical plug-in charging. The ability of drones to automatically recharge on approved charging pads extends their flight time and improves operational efficiency. Because it protects against dust and moisture and lessens connector wear, this technology extends the lifespan of drones. Continuous operations, which are essential for applications like infrastructure inspections, agriculture, and surveillance, are supported by wireless charging. The goal of ongoing developments in wireless charging technologies, such as resonant and inductive charging techniques, is to increase drone model compatibility, efficiency, and range.

4. Integrated Pest Management Using Drones

Integrated pest management (IPM) seeks to keep pest populations below economic injury levels through prevention, monitoring, and targeted interventions, while minimizing risks to the environment, human health, and non-target organisms. It prioritizes non-chemical approaches (e.g., habitat management and biological control), using pesticides only when necessary and in a risk-based manner. By reducing reliance on synthetic chemicals and leveraging ecosystem services, IPM supports biodiversity conservation and sustainable agricultural productivity [46,47].

IPM gained prominence following Rachel Carson's Silent Spring (1962), which drew attention to the ecological consequences of indiscriminate pesticide use. During the 1970s, agencies such as the USDA and FAO subsequently institutionalized IPM frameworks, emphasizing reduced reliance on synthetic pesticides and the adoption of more sustainable crop protection strategies [47,48]. Throughout the late 20th century, the integration of economic thresholds enabled farmers to make data-driven pest control decisions, a development further bolstered by emerging technologies like pheromone traps and biological pesticides, which improved IPM effectiveness [48,49]. Contemporary IPM is increasingly strengthened by precision agriculture, UAV-based monitoring, and climate-smart approaches that improve scalability and decision accuracy [50]. Large-scale programs such as FAO's Farmer Field Schools have expanded IPM capacity across diverse agro-ecological settings [51]. Despite persistent constraints, including resistance development and upfront implementation costs, current research is leveraging AI and machine learning to enhance prediction and optimize resource use, reinforcing IPM's role in sustainable pest management.

4.1. Principles of IPM

In the IPM framework, prevention and monitoring serve as the first line of defense, emphasizing pest-resistant crop varieties, crop rotation, and sanitation to preempt pest establishment, while regular inspections, pheromone traps, and predictive models facilitate early detection and informed intervention [52]. Biological control relies on natural enemies, such as predators, parasitoids, and pathogens, to suppress pests, thereby reducing dependency on synthetic inputs and preserving ecological balance. When other methods prove insufficient, chemical control is employed as a last resort, with strict adherence to targeted pesticide selection, optimal application timing, and recommended dosages to mitigate health and environmental risks and deter resistance [53]. Cultural practices, such as intercropping, adjusting planting times, and maintaining soil health further diminish pest survival and proliferation, whereas mechanical measures like barriers, traps, and hand removal disrupt pest habitats directly [54]. By orchestrating these diverse but complementary techniques, IPM sustains agricultural productivity and safeguards human health and the environment.

4.2. Economic and Ecological Benefits of IPM

IPM offers notable economic and ecological benefits compared to traditional pest control methods, primarily by integrating biological, cultural, physical, and chemical tools to manage pest populations in a cost-effective and environmentally sustainable manner. In terms of financial considerations, IPM often reduces overall expenses for farmers by emphasizing preventive measures and biological controls rather than relying on repeated applications of expensive chemical pesticides [55]. Additionally, research indicates that IPM can bolster crop yields and quality by containing pest populations without harming beneficial organisms, thereby improving marketability and increasing revenue [56]. From a resistance management standpoint, IPM's diversified strategies diminish the selective pressure that fosters pesticide-resistant pest populations, an issue frequently exacerbated by excessive chemical use [57]. Ecologically, IPM curtails pesticide runoff and collateral damage to non-target species, thereby preserving biodiversity and promoting a balanced ecosystem [58].

4.3. Challenges in Implementing IPM

IPM often encounters substantial hurdles related to both knowledge dissemination and the adoption of technology-driven solutions. Many farmers, particularly in developing regions, have limited educational opportunities, which can impede their understanding and application of complex IPM strategies; insufficiently funded agricultural extension services further compound this issue by conveying inconsistent or outdated information [59]. Moreover, cultural and linguistic diversity necessitates the tailoring of IPM outreach materials to local contexts and languages, underscoring the importance of context-specific communication approaches. On the technological front, integrating advanced tools, such as drones and AI, presents its own set of challenges, notably the high initial investment that can deter small-scale farmers from accessing financial support or incentives. Even when these tools are acquired, specialized training is necessary for their effective operation, and inadequate infrastructure, from unreliable internet connectivity to limited equipment maintenance services, can hinder the deployment and sustained use of modern IPM systems [60].

4.4. Multi-Technology Fusion Architecture for UAV-Enabled IPM

Effective integration of AI, UAVs, and IoT in IPM requires an architecture that can fuse heterogeneous data sources and translate model outputs into precise control actions. In typical deployments, multispectral or hyperspectral imagery captured by UAVs is first pre-processed to produce georeferenced maps of crop vigor and stress. These maps are then fused with ground-based sensor data, such as soil moisture, leaf wetness, temperature, and relative humidity measurements, using shared spatial coordinates and time stamps. Data fusion can occur at the feature level, where pixel-wise vegetation indices are augmented with interpolated ground-sensor readings, or at the decision level, where separate models trained on aerial and ground data are combined through ensemble or rule-based schemes. This multi-source fusion helps distinguish true pest- or disease-induced stress from abiotic factors (e.g., drought or heat stress), thereby reducing false alarms and increasing the reliability of IPM diagnoses.

However, implementing such integrated systems raises notable interoperability and standardization challenges. UAV platforms, cameras, and ground sensors are often supplied by different manufacturers, each with proprietary data formats, communication protocols, and coordinate systems. Without common standards for metadata, georeferencing, and time synchronization, aligning aerial imagery with in-field measurements becomes labor-intensive and error-prone. Similarly, AI decision-support software and precision sprayers may rely on incompatible file formats or closed APIs, limiting the seamless transfer of prescription maps and control commands. Addressing these issues requires the adoption of open data standards (e.g., standardized geospatial formats and sensor ontologies), interoperable communication protocols for IoT devices, and well-documented APIs that allow different components to exchange data securely and reliably. Progress in these areas will be critical for scaling integrated, AI-driven IPM systems beyond pilot projects and ensuring that technology-rich solutions remain robust, replicable, and accessible to diverse farming contexts [61,62].

4.5. IPM Adaptation and Efficacy

The global adoption of IPM has been driven by success stories, comparative research across diverse crops, and supportive government policies, all contributing to more sustainable and effective pest management in agriculture. Numerous examples illustrate IPM's efficacy in reducing pesticide use and boosting crop yields. In the United States, the Northeastern IPM Center has documented notable achievements across various crops, such as in apple production, where IPM strategies have effectively controlled pest populations while minimizing chemical inputs [63]. Similarly, in India, the National Research Centre for Integrated Pest Management (NCIPM) has highlighted successful outcomes in maize cultivation, including a case study. These examples underscore the global relevance of IPM as an adaptable framework that enhances productivity and sustainability.

Comparative studies across different crop types reveal the tailored application of IPM methods. For instance, multi-national research on rice cultivation emphasizes biological control of lepidopteran pests, demonstrating the importance of understanding pest biology and ecology to develop targeted [64]. Likewise, in horticultural crops, the Northeastern IPM Center has documented instances where habitat manipulations, such as introducing beneficial organisms, reduced pest infestations and minimized pesticide usage [65]. Although core IPM principles remain consistent, specific techniques vary based on crop characteristics and pest dynamics. Government initiatives further strengthen IPM's adoption and efficacy. In the USA, the USDA developed the National Road Map for IPM, outlining strategic directions for IPM research and implementation. Simultaneously, the U.S. Fish & Wildlife Service has mandated IPM in pest management decisions, facilitating coordination among farmers, researchers, and policymakers [66]. These policies provide a structured framework for IPM and foster collaboration to promote sustainable agricultural practices worldwide.

4.6. Summarized Analysis

In order to move beyond purely qualitative descriptions and provide a clearer understanding of the performance and limitations of current solutions, we compiled a quantitative comparison of representative AI-assisted UAV technologies used for crop disease and pest detection, precision spraying, and livestock monitoring. The studies summarized in Table 5 report key metrics such as detection accuracy, mean average precision, pesticide-use reduction, and monitoring accuracy, allowing direct comparison across different sensor configurations and AI models.

Table 5. Quantitative comparison of AI-assisted UAV technologies for crop protection and livestock monitoring.

Sensor Modality	AI Model	Application	Key Quantitative Results	Benefits	Key Limitations/ Challenges
RGB or multispectral imagery [67]	CNN classifiers, U-Net/segmentation networks	Early detection and quantification of leaf diseases in major crops	Classification accuracy often above 90–98%; F1-scores typically > 0.9; disease severity quantified with pixel-level infection estimates ranging from about 0.7% to 14% in field trials	High detection accuracy, ability to localize severity, scalable to large image volumes	Performance may degrade for unseen cultivars or lighting conditions; requires labeled datasets and periodic retraining
Multispectral/hyperspectral + spray system [64]	Deep learning pest detection with variable-rate spraying controller	Mapping pest/disease hotspots and adjusting pesticide dosage in real time	UAV deep learning systems achieve pest identification accuracy of about 89–94%; precision spraying systems report 20–30% or even 30–70% reductions in pesticide use compared with blanket treatments, while maintaining effective pest control	Significant chemical savings, reduced environmental impact, better targeting of affected zones	Accuracy drops to 60–70% under strong light or occlusion; spray drift and regulatory constraints limit operation; edge devices must balance inference speed and battery life
Spray boom with GPS guidance [68]	Flight-path optimization and spray analysis tools	Comparison of multi-rotor UAVs with piloted aircraft for pesticide application	Studies report comparable pest control efficacy and acceptable spray coverage for multi-rotor UAVs relative to conventional aircraft, with differences in droplet deposition patterns and residues depending on configuration and conditions	Flexible low-altitude operation, suitability for small/fragmented fields, reduced pilot risk	Smaller payload and shorter endurance than manned aircraft; spray pattern more sensitive to wind and setup

5. Drone Applications in Smart Agriculture

Modern farming innovations like drones, AI-driven systems, and self-operating equipment have surfaced to tackle productivity issues in an eco-friendly and expandable way. These advancements enhance operational efficiency while also fostering precision agriculture, promoting environmental sustainability, and enabling informed decision-making based on data. Drone technologies reduce the need for excessive amounts of water, pesticides, and herbicides; preserve soil fertility; aid in the effective use of labor; increase productivity; and enhance quality. Some applications of drone technology are given in Figure 5.

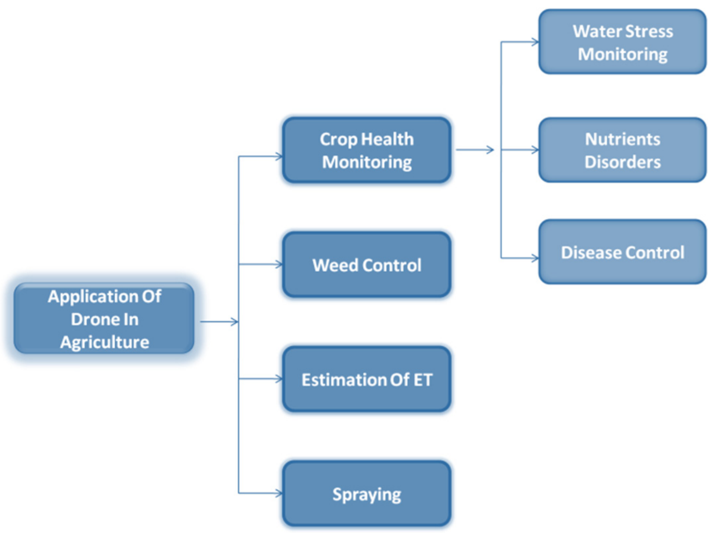

Figure 5. Applications of drones in agriculture and pest control.

5.1. Soil Fertility and Productivity Management

Drones have revolutionized the management of soil fertility in contemporary agriculture. Drones, outfitted with multispectral and hyperspectral sensors, gather complex images that reveal essential parameters, such as moisture levels, nutrient deficiencies, plant stress, and the overall health of the soil. The datasets are transformed into detailed soil maps, allowing farmers to pinpoint areas that need specific fertilization, irrigation, or other necessary actions. This encourages the effective utilization of resources and fosters environmentally friendly farming methods.

To advance in-field soil analysis, Nguyen, T.H et al. [69] developed a GPS-guided autonomous soil testing rover equipped with sensors that measure pH, electrical conductivity, moisture content, and temperature. The rover incorporates self-directed navigation and obstacle detection, relaying information instantaneously to an online platform for evaluation and agricultural suggestions. The validation results indicated that the rover's temperature readings were in close agreement with manual thermometers. Minor discrepancies in moisture readings were linked to environmental conditions and latency, suggesting a high level of reliability. In addition to this, DeBruin, J. et al. [70] employed soil moisture sensors in conjunction with neural network algorithms to adaptively modify irrigation levels. Their system enhanced agricultural productivity, conserved water resources, and offered valuable information for strategizing in response to seasonal changes. In a similar vein, Vijayalakshmi, R. et al. [71] created a system for monitoring soil moisture that incorporates a Decagon EC-5 sensor, a nRF24L01 wireless transmitter, and a microprocessor. This configuration enabled the wireless transmission of data using a 2.5 GHz signal, facilitating real-time monitoring through an RS232 computer interface.

Qu et al. [72] developed a rapid inversion model to assess deep soil moisture (0–200 cm) in dryland agriculture, focusing on drone-based sensing techniques. Through the correlation of canopy leaf moisture and surface moisture via regression models, they achieved a notable enhancement in moisture prediction accuracy, particularly at a depth of 20 cm. This method establishes a crucial basis for successful precision agriculture in dry areas. Historically, assessing the quality of soil tillage depended on manual sampling methods, which are both labor-intensive and lack precision across extensive regions. Advancements like laser scanning tools have enhanced the evaluation of surface roughness, yet drones now provide more scalable and automated options. Drones equipped with AI technology are capable of assessing soil attributes such as moisture content, nutrient levels, and fertility, which aids in making informed choices regarding crop selection, irrigation, and fertilization strategies. Furthermore, drones significantly improve the monitoring of field conditions, particularly in expansive paddy fields that pose challenges for manual observation. Through precise and extensive observation, agricultural producers can minimize physical effort and alleviate stress. The integration of AI with data gathered by drones enhances land usage planning, crop rotation strategies, and infrastructure management, leading to significant improvements in agricultural efficiency and resilience.

5.2. Aquaculture Monitoring by Drone

Drones are revolutionizing habitat monitoring and fisheries management through AI, sensor technology, and engineering advancements, offering cost-effectiveness, real-time monitoring, and broader coverage, but also facing challenges like data processing and regulatory issues. A study developed an autonomous drone system that is cloud-integrated and specially made for aquaculture surveillance [73]. Through the integration of deep learning models into a cloud-based architecture, this system efficiently interprets aerial imagery to identify people, boats, cages, and fish behavior. It adds intelligent features like fish counting and feeding intensity evaluation to improve aquaculture operations. Chan et al. [16] introduced automated water quality monitoring in net cage aquaculture with a drone-based system. A hexacopter equipped with a camera, computer, flight control board, servo motor, and GPS auto-cruise is used in the system. It gathers data on water quality, determines distances, and recognizes net cages using a modified YOLO deep learning model. An innovative IoT architecture called the Hybrid Aerial Underwater Robotic System (HAUCS) was created to upgrade the aquaculture field. The HAUCS mobile sensing platform's most recent advancements center on its useful application in pond farms that are currently in operation. To increase platform stability and expand the HAUCS's environmental sensing capabilities, a unique stiff Kirigami-based robotic extension is designed.

5.3. Crop Monitoring

The major challenge in farming is the combination of large areas and ineffective crop monitoring. Observing increasingly erratic weather patterns makes problems worse by increasing risk and field maintenance expenses. During the crop season, drones can monitor crop conditions so that prompt, need-based action can be taken. It is possible to calculate various multispectral indices based on the reflection pattern at different wavelengths by employing many types of sensors related to visible, near-infrared, and thermal infrared radiation. Crop problems like water stress, nutritional stress, insect pest attacks, illnesses, etc., can be evaluated using these indices. Even before outward symptoms manifest, the sensors on the drones can detect the prevalence of illnesses or deficiencies. As a result, they are a tool for early disease identification. Drones can observe the crop with different indices [74].

Drones provide real-time data on agricultural conditions, enabling farmers to make informed decisions about irrigation, insect management, and fertilization, thereby improving crop quality and yield. The importance of crop monitoring and management is that crop monitoring enables farmers to check the health and growth of their crops in real time, allowing them to better manage resources like water, fertilizers, and pesticides. Farmers may save money and decrease waste by accurately directing inputs where they are most needed [75].

5.4. Precision Pest Management

Actuation drones could aid in controlling the pests at these hotspots, while sensing drones could assist in identifying pest hotspots. It may be possible to control insect hotspots by applying pesticides at varying rates. Although pesticides have been sprayed from aircraft for decades, a significant portion of the products is lost to drift and is spread across wide distances [76]. Both human health and terrestrial and aquatic ecosystems are at risk from this [73]. Spray drift is mainly caused by weather (e.g., wind direction and speed), application techniques (e.g., spray height above the canopy), and droplet size (e.g., nozzle type and product composition) [77,78]. According to empirical and modeling research, spray drift into non-target locations can be significant [78,79]. Thus, there is a need for better ways to apply pesticides, and drones may be used to apply insecticides and matricides precisely.

Drones have several advantages over manned crop dusters, including the ability to reduce spray spread, lower operator exposure to pesticides, and relative simplicity of deployment [80]. The drones make it possible to control pests with high precision and effectiveness. The main benefit of pest management using drones is that they have sensors for imaging that can identify pest-infected areas accurately. This compensates for pesticide application, which is aimed at lowering the use of chemicals and the detrimental impact on species that are a vital element of nature and the environment.

Drones that automate insect detection and pesticide application significantly reduce the workload and costs associated with manual spraying methods. This method allows large areas to be covered fast, reducing the amount of time and physical effort required, which was expected to be massive [81]. This strategy resulted in lower levels of environmental contamination and reduced pesticide exposure among farmers. Thus, it promotes itself as a healthy agricultural environment. Drones furnish high-resolution imagery and real-time data that facilitate the monitoring of pest activity and crop health. This richness of information enables better-informed decision-making, ensuring that it improves the effectiveness of pest management tactics. Since drone technology has become increasingly accessible and cost-effective, its adoption in pest control is expanding. Drones not only bolster sustainable agricultural practices but also harmonize with environmental conservation efforts. Drone technology is leading the way, and the future of pest management seems optimistic.

5.5. Cattle Locating Using Drone Technology

Drones are now used for cattle tracking. They can navigate large terrains independently; can find and track cattle over large areas, which is hard for humans; and helps with tasks like counting and identifying individual animals. All these AI-assisted drones use convolutional neural networks (CNNs) to identify animals in complex environments and evaluate photographs with high accuracy [80]. These aerial gadgets make it possible to monitor cattle in real time, reducing significant amounts of time and effort. Drones with specific cameras and sensors can also monitor cattle's health. Figure 6 shows pest management and cattle monitoring in agriculture using drones. Drones should be sturdy enough to resist diverse weather conditions, which is vital, especially when faced with strong wind currents [82]. The associated software should be easy to use and provide essential features designed specifically for ranch management. They ought to have the ability to monitor the general dynamics of the herd and precisely track individual animals. A case study from Spain showed how drones with sophisticated networking and imaging systems could effectively monitor cattle in a designated area. The agricultural sector is poised to benefit from further advancements in drone and sensor technologies, which might lead to even greater improvements in livestock management and operational efficiency.

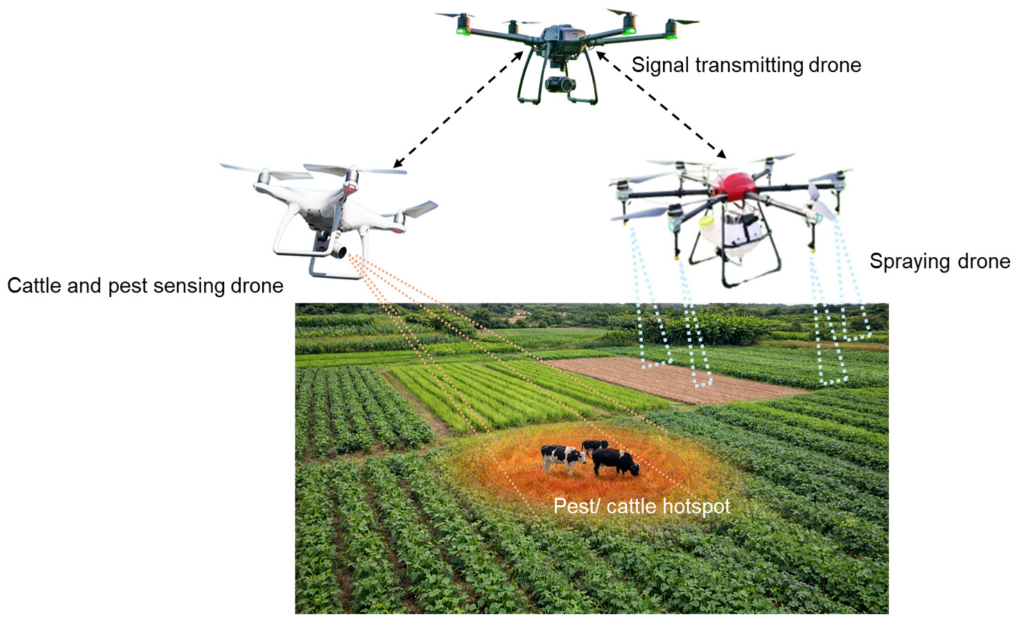

Figure 6. Sensing drones for detection of pest hotspots and cattle.

In extensive farming systems, this investigation illustrates the potential of deep learning and drones for automated cattle monitoring. Researchers could reliably identify Canchim cattle (similar to the Nelore breed) even in suboptimal conditions by testing 15 CNN architectures on 1853 aerial images containing 8629 cattle samples. Barbedo et al. [4] presented a cattle counting method that employs drone-captured images, incorporating deep learning for initial detection, color space manipulation for improved contrast, and morphological operations to separate animals into clusters. It also considers image overlap through the use of image matching. The method was effective for livestock monitoring in large areas, as it achieved over 90% accuracy across varied conditions and backgrounds when tested on Nelore and Canchim breeds.

5.6. Drone-Based Plant Disease Detection Systems

The use of image-based Drones for plant disease detection has emerged as a promising solution in precision agriculture. Using machine learning and deep learning techniques, these systems facilitate efficient crop monitoring, early disease detection, and cost-effective diagnosis. A study [83] proposed a DCNN-based method for automated yellow rust detection in high-resolution drone images. The model uses spatial and spectral data and Inception-Resnet layers for feature extraction. In a controlled field experiment, it outperformed random forest classifiers, achieving an overall accuracy of 0.85. The study suggests that integrating spectral and spatial information improves disease detection precision. Zhao et al. [84] introduced an automated pest disease detection method using drone-captured images, where a deep learning-based strategy is used to overcome image blur and object sizes. When tested on a bespoke dataset of 42,452 wormhole annotations, the technique outperformed existing detection methods, with an overall accuracy of 87.2% AP50 and 94.7% R-squared.

5.7. Soil Quality Monitoring

In precision agriculture, soil quality monitoring has been transformed by recent developments in drone technology [85,86], as well as high-resolution imaging and machine learning. This research [87] used drone-based multimodal data and found that data fusion, particularly thermal and multispectral data, improved SMC estimation accuracy. The RFR model showed superior performance, particularly during the vegetative stage, suggesting the potential of drone-based data for improved farm-scale irrigation scheduling. Additionally, they used machine learning algorithms like random forest regression, K-nearest neighbor, and partial least squares regression to estimate SMC in a maize field over two years. Using high-resolution aerial imaging (HRAI) and machine learning algorithms, Jia et al. [88] introduced a novel approach to soil contamination mapping. It implements four algorithms and utilizes 1068 soil samples from an arsenic-contaminated region in China. In predicting the risk of contamination, the extreme random forest algorithm outperforms others, achieving an accuracy of 0.87. Another study [89] used multispectral imagery to monitor the total nitrogen content of silage corn soil using unmanned aerial vehicles. The PLSR model is effective for TN inversion, while the SVM-RFE algorithm aids in selecting critical vegetation indices. The mature growth stage yields the most precise results. The applications are summarized in Table 6.

Table 6. UAV-enabled applications summarized as sensing–analytics–action pipelines.

Application Domain	Typical Data & AI Output	Primary Action	What to Report (Metrics + Constraints)
Nutrient/fertilizer management	Multispectral/hyperspectral; N stress indices; prescription maps	Variable-rate fertilizer plan; targeted scouting	Prediction error + uncertainty; fertilizer reduction; yield response; payback/ROI; calibration cost
Irrigation & water stress	Thermal + multispectral; water stress map	Irrigation scheduling; leak detection	Detection accuracy; water-use efficiency; thermal calibration; weather sensitivity
Pest & disease monitoring	RGB/multispectral; detection/segmentation; risk scoring	Threshold-based intervention; scouting	Precision/recall; robustness under lighting/occlusion; decision cost of errors
Precision spraying (pesticides/biocontrol)	Prescription map + telemetry; flow/path control	Spot/variable-rate spraying	Deposition uniformity; drift risk; coverage rate (ha/h); chemical reduction; regulation
Livestock monitoring	RGB/thermal video; counting/re-ID/anomaly flags	Herd localization; welfare alerts	Counting/ID error; disturbance risk; battery/coverage limits; privacy
Aquaculture monitoring	RGB video; feeding intensity/anomaly detection	Feeding control; health alerts	Feeding efficiency; false-alarm rate; glare/waves; platform stability

6. Case Studies in Smart Agriculture

Although these case studies discuss some successful applications of digital and UAV-based technologies, they are mostly told as pilot or localized applications. Thus, this section critically evaluates their implementation issues, performance measures they report, and constraints, instead of showing their implementation as a solution that can be universally applied. Farmers can incorporate cutting-edge digital tools into their daily operations, particularly in isolated and underserved areas, when they have dependable and fast internet access.

6.1. Enabling Infrastructure: Starlink in Bangladesh

The official launch of Starlink in Bangladesh creates new prospects for agricultural innovation [90]. This development is expected to significantly enhance internet connectivity in rural and remote areas of Bangladesh, offering farmers access to global markets, real-time weather updates, and precision farming tools. Nevertheless, there are few quantitative studies on the improvement of yield or cost reduction that can be linked to the implementation of Starlink-enabled connectivity. The obstacles that may limit the large-scale adoption include the subscription fees, the affordability of the equipment to smallholder farmers, and the control procedures that need to be approved. There has been no systematic analysis of long-term effects on the economic viability and productivity of farms.

6.2. Drone-Based Nitrogen Monitoring in Corn Fields (USA)

The University of Minnesota in the USA implemented drone technology [91] to optimize nitrogen management in corn fields. Nitrogen levels were monitored during various growth stages using drones equipped with multispectral sensors. The data collected was instrumental in developing prescription maps for variable-rate nitrogen application, which guarantees the precise use of fertilizer. The investigation demonstrated that the utilization of drones for monitoring resulted in a decrease in fertilizer consumption, a reduction in environmental impact, and an increase in crop yield by facilitating the application of nitrogen more effectively. Although these advantages were reported, there were some issues with implementation, such as the reliance on good weather conditions, the ability of the UAV to fly over a limited distance, and the fact that the multispectral data has to be processed by a specialist. Though a decrease in the use of fertilizers and an increase in yield were reported, long-term assessment of the growing seasons and cost–benefit analysis were not regularly performed.

6.3. Drones in Precision Agriculture for Soil Health (Australia)

Farmonaut is a satellite-based, cutting-edge technology in Australian agriculture that helps farmers optimize operations, increase crop yields, and adopt sustainable practices [92]. Farmonaut is revolutionizing Australian agriculture with this innovative technology. High-resolution data is collected by farmers across their fields using drones. The analysis of this data enables the identification of soil moisture variations and nutrient deficiencies. Monitoring with drones has enhanced crop yields, targeted fertilization, and optimized irrigation, all while minimizing environmental impact and reducing costs. The integration of drone technology in Australian agriculture is improving farm productivity, promoting sustainability, and enhancing soil health management. However, data processing infrastructure, farmer training, and integration with current farm management techniques are necessary for the scalability of such UAV-based soil monitoring systems. The cited research still lacks long-term evaluations of soil health improvement and quantitative performance measures.

6.4. Drones in Floral Industry (South Africa)

Researchers created a system to monitor Explorer rose crops that combine deep learning algorithms with unmanned aerial vehicles [93]. They were able to identify open and closed rosebuds with a mean average precision of 94.1% and a strong correlation (R2 = 0.998) with manual counts by analyzing drone-captured videos. By reducing physical contact, this method maximizes harvest timing and preserves flower quality. In South Africa's mountainous Cape Floristic Region [94], Protea farmers face challenges with traditional monitoring methods. Furthermore, the long-term maintenance needs and economic viability of such deep learning-based monitoring systems were not carefully considered, which make it possible to effectively monitor crop conditions and plant health across vast, challenging terrain. This technology improves data accuracy and lowers labor intensity.

The case studies were selected from the reviewed corpus to illustrate different layers of the UAV value chain: enabling infrastructure, sensing-to-prescription workflows, and application-specific deployment in high-value crops. To improve comparability, Table 7 summarizes case studies with their social impact and application, and Table 8 reports a common set of indicators; where a source does not report a metric (such as ROI), it is marked as not reported, and the recommended measurement is stated.

Table 7. Summaries of case studies with their social impact and application.

Case/Country	Challenges	Performance Indicator	Social Impact	Application
Drone-based nitrogen monitoring in corn, USA	Rural and remote areas lack reliable, fast internet; digital divide between urban and rural communities.	Availability of high-speed, low-latency internet in underserved regions; number of live users and farms; ability to run real-time digital tools like weather, advisory apps.	Better access to information and online services for farmers, students, and rural entrepreneurs; potential increase in income through access to wider markets and digital financial services; reduced digital divide.	Satellite internet backhaul, smart-farming, IoT sensors, remote advisory, e-commerce for farm products, and resilient communication during disasters.

Table 7. *Cont.*

Case/Country	Challenges	Performance Indicator	Social Impact	Application
Drone-based soil and crop monitoring (Farmonaut- satellite based system), Australia	Variability in soil moisture; need to manage water scarcity and fertilizer efficiency; manual scouting is time-consuming.	High-resolution maps of soil moisture and nutrient-related indices; sustainable water and fertilizer use, reduced production costs, and improved resilience to drought; support for environmentally responsible farming practices, specific fertilization plans.	Improved worker safety and reduced physical strain; better harvest timing, improves quality and market value of flowers; more consistent supply for the floral value chain.	UAVs flying over rose fields to capture video; deep learning algorithms to count buds and provide decision support for harvesting and crop management.
Drones in Protea production, mountainous Cape Floristic Region, South Africa	Limited visibility of crop conditions across large, uneven landscapes.	Enhanced spatial coverage and accuracy of crop health data using RGB and multispectral imagery; fewer field visits needed; better detection of stress or disease hotspots.	Reduced labor demand; better protection of high-value Protea crops; potential income stability for farmers in remote mountainous areas.	Drone-based remote sensing for monitoring plant health, detecting stress, and guiding targeted interventions

Table 8. Case studies summarized with standardized indicators and replicability constraints.

Case	Objective	Technical Outcome Reported	Economic Outcome Reported	Replicability Constraints	Relevance to IPM/ Inputs
Connectivity enablement (Bangladesh; satellite internet context)	Enable real-time advisory/IoT/UAV workflows	Coverage/latency: reported in source	ROI: not reported	Affordability; power reliability; regulation	Enables near-real-time prescriptions and logging
UAV-based N monitoring (maize; USA)	Support variable-rate nitrogen decisions	Prescription accuracy: reported in source	Fertilizer savings/ROI: not reported	Calibration; season/variety differences	Input optimization (fertilizer)
Large-farm analytics platform (Australia)	Soil/crop monitoring for decisions	Indices/maps: reported in source	Cost reduction: not reported	Data ownership; training; connectivity	Input optimization (water/fertilizer)
High-value floriculture monitoring (South Africa)	Stress detection and harvest support	Detection/coverage: reported in source	Labor savings: not reported	Terrain/weather; local skills	Targeted interventions and scheduling

6.5. Future Directions in Smart Agriculture

Deeper integration of robotics, IoT, AI, and satellite-based connectivity will propel the next wave of smart agriculture. In rural areas, innovations like Starlink are expected to improve internet connectivity, enabling real-time monitoring and the use of cloud-based tools. While blockchain technology will offer traceability and transparency across the supply chain, artificial intelligence will enhance crop disease detection, forecast yields, and enable automated spraying. Together, these developments seek to improve productivity, lessen their negative effects on the environment, and guarantee long-term food security. As these technologies mature, robotics will play an increasingly significant role in automating routine farming tasks, such as planting, harvesting, and crop monitoring. Autonomous machinery, including drones and robotic harvesters, will allow farmers to perform these tasks more efficiently and with fewer labor inputs. Additionally, the integration of IoT will allow for constant data flow from sensors embedded in soil, crops, and machinery. This data will enable farmers to make informed, real-time decisions that improve productivity while reducing waste and costs.

In the future, data-driven agriculture will shift from being reactive to more predictive. AI will use big data analytics to anticipate possible yield threats, like pest outbreaks or unfavorable weather conditions, before they happen, in addition to responding to crop health issues. Tools for precision agriculture will advance, providing highly customized advice on pest management, fertilization, and irrigation. Farmers will be able to conserve water, minimize chemical inputs, and maximize resource use as a result, all of which will contribute to environmental sustainability.

Future research should move beyond accuracy-centric prototypes toward validated, interoperable, and economically grounded systems. Table 9 outlines specific entry points aligned with near, mid, and long-term horizons.

Table 9. Roadmap with specific bottlenecks and actionable research entry points.

Horizon	Priority Goal	Concrete Tasks	Measurable Success Criteria
Short term (0–2 years)	Reliable field validation	Multi-site benchmarks; standardized reporting; uncertainty estimation	Public benchmark datasets; multi-site eval; KPI reporting
Short term (0–2 years)	Edge inference readiness	Model compression; efficient architectures; energy-aware scheduling	Latency < target; battery impact quantified
Mid term (2–5 years)	Closed-loop IPM pilots	Integrate thresholds + prescriptions + variable-rate actuation	Demonstrated chemical reduction with maintained yield
Mid term (2–5 years)	Interoperability and standards	Metadata standards; open interfaces to FMIS platforms	Cross-vendor pipeline works end-to-end
Long term (5+ years)	Autonomous routine operations	Docking stations; safe autonomy; swarm coordination	Regulatory approval; high uptime; safety incidents near zero
Long term (5+ years)	Inclusive deployment models	Service-based models for smallholders; cooperative ownership	Adoption growth; positive ROI in smallholder contexts

7. Conclusions

AI-assisted drone technology stands at a critical juncture where technical capability meets real-world application. Its potential to transform precision agriculture into a more data-driven, resource-efficient, and environmentally sustainable practice is clear. Yet, the gap between technological promise and widespread adoption remains substantial, shaped not only by engineering challenges but also by economic realities, institutional readiness, and the diversity of farming contexts across the globe.

Bridging this gap will require shifting the research focus from isolated technical advancements toward integrated, systems-level solutions. Priorities should include extending operational endurance through hardware innovation, developing adaptive and interpretable AI models suited to variable field conditions, and establishing interoperable platforms that seamlessly connect drone-derived data with existing farm management tools. Equally important is the generation of robust, context-specific evidence through long-term field trials that capture agronomic, economic, and operational outcomes across different scales and regions.

Ultimately, the successful integration of AI-assisted drones into agriculture hinges on more than technological refinement. It demands deliberate, inclusive innovation strategies that account for regulatory frameworks, data governance, and equitable access. Without parallel investments in capacity building, supportive policy environments, and interdisciplinary collaboration, spanning engineering, agronomy, economics, and the social sciences, the risk of exacerbating existing inequalities in agriculture remains high.

If thoughtfully deployed and contextually adapted, AI-assisted drones can contribute meaningfully to addressing pressing global challenges in food security, climate resilience, and environmental sustainability. Realizing that contribution, however, will depend on how deliberately the research, policy, and agricultural communities work together to ensure these technologies are not only advanced but also accessible, appropriate, and beneficial for the diverse farmers who stand to gain the most.

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