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REVIEW

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# The expanding role of multirotor UAVs in precision agriculture with applications AI integration and future prospects

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**Abstract**
The adoption of unmanned aerial vehicles (UAVs), particularly multirotor systems, is transforming precision agriculture (PA) by enabling versatile and cost-effective real-time, high-resolution data collection. This review aims to provide a comprehensive overview of the classification, applications, and advantages of multirotor UAVs in PA. A thorough literature survey and comparative analysis were conducted to examine recent technological innovations, challenges, and economic potential associated with these UAVs. The findings highlight that multirotor UAVs equipped with advanced sensors, artificial intelligence, and machine learning techniques improve crop monitoring, disease detection, and resource management. Despite challenges such as limited flight duration, payload constraints, regulatory issues, and data processing complexities, emerging advancements like improved battery technology, IoT integration, and UAV swarm operations show promise in overcoming these limitations. This study offers insights to guide future research and support sustainable agricultural practices, particularly in developing regions.

**Article Highlights**

- Multirotor drones are transforming farming by enabling fast and precise crop monitoring and management.
- Smart sensors and AI help detect pests and diseases early, improving yield and reducing chemical use.
- The study outlines future drone innovations to support sustainable agriculture in developing regions.

**Keywords** Unmanned aerial vehicles, Precision agriculture, Multirotor UAVs, Crop health monitoring, Artificial intelligence in agriculture, UAV swarms, Remote sensing, Smart farming

## 1 Introduction

Precision agriculture (PA) signifies a transformative shift in farming practices, characterized by the strategic application of technology to enhance agricultural productivity and sustainability [1, 2]. This data-driven methodology leverages advanced tools and techniques to manage crops and resources more efficiently, leading to increased yields and reduced environmental impacts [3, 4]. Among the most impactful technologies in this domain are UAVs, commonly referred to as drones. Within the UAV category, multirotor variants—equipped with multiple rotors—have emerged as particularly valuable instruments in PA due to their remarkable versatility and adaptability [5, 6]. Multirotor UAVs possess several advantages over fixed-wing counterparts, primarily attributed to their ability to hover, navigate tight spaces, and operate at lower altitudes [7]. These features make them particularly suitable for capturing high-resolution imagery and conducting detailed aerial surveys. The integration of advanced sensors, such as multispectral cameras and thermal imaging systems, allows multirotor UAVs to provide critical insights into crop health, soil conditions, and various environmental factors influencing agricultural outcomes [8]. This enhanced observational capacity empowers farmers to make more informed decisions, optimize resource utilization, and improve farm management.

Recent technological advancements have significantly expanded the capabilities of multirotor UAVs. Innovations such as automated flight systems and autonomous operations have streamlined data collection processes, reducing the need for manual intervention and enabling more frequent and consistent monitoring [9]. Furthermore, the integration of UAV technology with geographic information systems (GIS) and remote sensing (RS) has facilitated the creation of detailed maps and models, thereby enhancing PA practices [8]. These advancements effectively address complex agricultural challenges with unprecedented accuracy and efficiency. Despite these promising developments, integrating multirotor UAVs into PA faces several challenges. Regulatory hurdles constitute a major obstacle, as UAV operations must navigate a complex array of aviation regulations, airspace restrictions, and privacy concerns. This can complicate the implementation of UAV technology for agricultural operators, potentially limiting its widespread adoption [10]. Moreover, issues such as battery life and flight duration remain significant constraints; although improvements in battery technology have extended flight times, effectively covering expansive agricultural areas continues to pose challenges, impacting the practicality and cost-effectiveness of UAV deployments [11]. Also, data management and analysis emerge as critical concerns, as the vast amounts of data generated by high-resolution sensors necessitate sophisticated processing and analytical tools to extract meaningful insights, imposing substantial financial and logistical burdens on farmers (Fig. 1).

Beyond agriculture, UAVs are increasingly utilized in various sectors such as smart cities, infrastructure monitoring, environmental conservation, and disaster management. In smart cities, UAVs play crucial roles in traffic monitoring, urban planning, and infrastructure inspection by providing real-time data and facilitating efficient resource management [12]. These versatile applications highlight the broader potential of UAVs as transformative tools across diverse fields, underscoring the importance of continued innovation and research in UAV technologies [13].

The potential for multirotor UAVs in PA is promising, with emerging trends and advancements poised to address existing limitations and broaden UAV applications [5]. Next-generation UAVs featuring enhanced capabilities—such as longer flight durations, increased payload capacities, and advanced sensing technologies—are on the horizon. The integration of AI and ML is expected to further improve data processing and decision-making, allowing for more responsive and adaptive farming practices [14, 15].

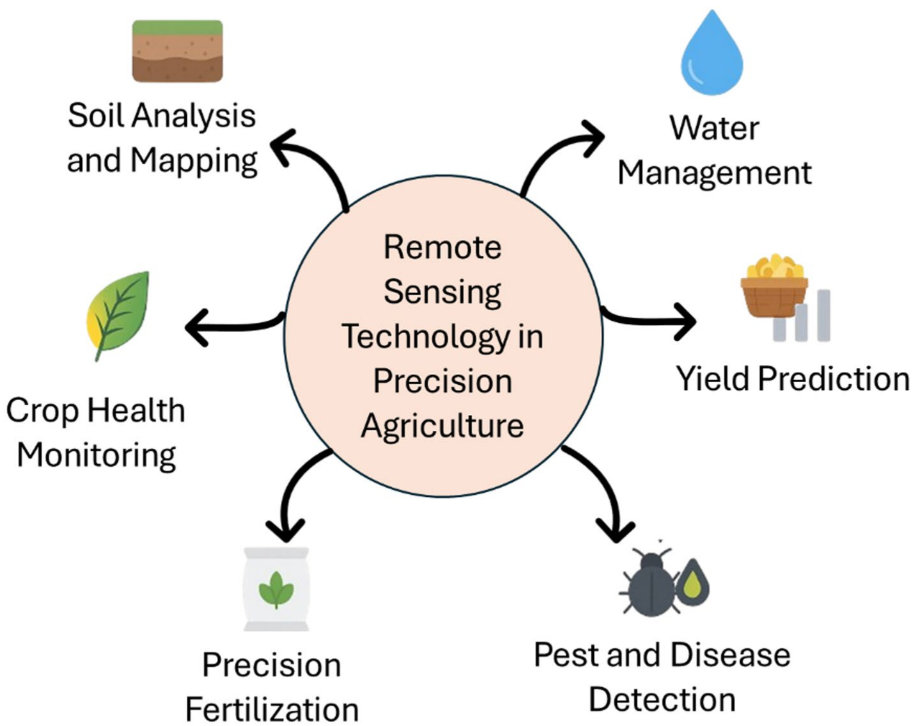


**Fig. 1** Key applications of RS Technology in PA

While previous reviews have broadly discussed UAVs in agriculture, this paper specifically addresses a notable gap by conducting a detailed comparative analysis of multirotor versus single-rotor UAVs and synthesizing the most recent technological advancements and challenges associated with multirotor UAV deployment. This comparative focus on multirotor UAVs' unique contributions—such as their agility, operational flexibility, and suitability for high-resolution data collection—differentiates our review from earlier studies that either generalize UAV applications or focus solely on fixed-wing systems. Additionally, this review identifies key research gaps, including limited analyses of real-world data processing challenges, cost–benefit considerations in developing regions, and integration of emerging technologies such as AI-enabled UAV swarms and internet of things (IoT)-based agricultural networks. By highlighting these areas and proposing directions for future research, this paper aims to serve as a valuable resource for researchers, practitioners, and policymakers exploring the transformative potential of multirotor UAVs in sustainable agriculture.

Several literature reviews have been published on the use of UAVs in PA, focusing on topics such as UAV types, sensor integration, image processing algorithms, and application-specific case studies [16, 17]. However, many of these reviews either emphasize fixed-wing UAVs, lack classification based on rotor configurations, or do not delve into the recent integration of multirotor UAVs with AI, IoT, and VRT for smart farming applications. Table 1 provides a comparative summary of existing literature reviews on UAVs in PA, focusing on their scope, UAV types, technologies covered, and identified gaps. It highlights how the present review uniquely emphasizes multirotor UAVs, offering rotor-based classification, technological integrations, and a roadmap for future innovations.

This paper provides an in-depth overview of the classification of UAVs, focusing on the specific roles and advantages of multirotor UAVs in PA. It examines how these UAVs

**Table 1** Comparison of existing literature reviews on UAVs in PA

| Sr. No | Scope | UAV focus | Technologies covered | Gaps identified | References |
|---|---|---|---|---|---|
| 1 | UAVs for remote sensing | Mixed (fixed-wing, rotary) | Imaging, NDVI | Limited focus on multirotor-specific applications | [18] |
| 2 | AI in agriculture | General UAV overview | AI, ML, data fusion | No classification of UAVs or platform-specific review | [19] |
| 3 | UAV-based crop monitoring | Multirotor only | Thermal and multispectral | Did not address future tech integrations like blockchain or swarm UAVs | [20] |
| 4 | Multirotor UAVs for PA | Multirotor only | Classification, applications, AI, IoT, VRT, Blockchain | Offers rotor-based classification, challenges, future trends, and innovation roadmap | This review |

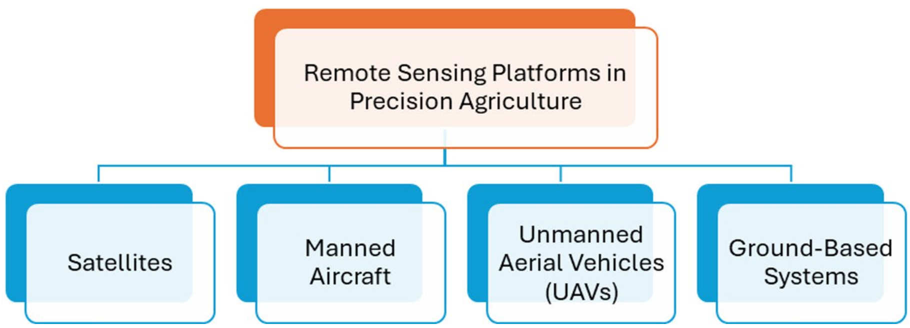


**Fig. 2** RS platforms in PA [24, 25]

have transformed agricultural practices by enabling more accurate monitoring, analysis, and management of crops and resources. Additionally, the paper includes a comparative analysis of multirotor and single-rotor UAVs, highlighting their respective performance characteristics, benefits, and limitations. Through this comparative approach, the paper aims to elucidate the unique contributions of multirotor UAVs and their impact on modern farming practices. By exploring recent advancements, current challenges, and future prospects, this review seeks to provide a comprehensive understanding of how multirotor UAVs are shaping the future of PA.

### 1.1 Precision agriculture

PA utilizes diverse platforms for data acquisition and management, where RS technologies are essential for crop monitoring, soil analysis, and environmental assessment [21, 22]. Key RS platforms include satellites, manned aircraft, ground-based systems, and UAVs—each offering unique strengths and trade-offs in terms of cost, resolution, flexibility, and ease of deployment [21, 23].

Figure 2 illustrates these platforms, highlighting their varied capabilities, and influencing their suitability for specific PA tasks such as high-resolution crop health mapping, large-scale soil surveys, and real-time environmental monitoring for precision interventions.

Table 2 provides a comparative analysis of RS platforms commonly used in PA, highlighting key parameters such as flexibility, cost, accuracy, and deployment feasibility. Each platform—satellites, manned aircraft, ground-based systems, and UAVs—exhibits unique strengths; for instance, UAVs offer very high flexibility and adaptability with moderate cost, while ground-based systems provide high accuracy but involve greater

**Table 2** Comparison of RS platforms in PA [2]

| Sr. No | Parameters | Platform | | | |
|---|---|---|---|---|---|
| | | Satellites | Manned aircraft | Ground-based systems | UAVs |
| 1 | Flexibility | Low | Moderate | High | Very high |
| 2 | Adaptability | Moderate | High | Moderate | Very high |
| 3 | Cost | High | Very high | Moderate | Moderate to low |
| 4 | Time Consumption | Low | Moderate | High | Moderate |
| 5 | Risk | Low (but weather-dependent) | Moderate | High (labor-related) | Moderate |
| 6 | Accuracy | Moderate | High | Very high | High |
| 7 | Deployment feasibility | High | Moderate | Low | High |
| 8 | Availability | Moderate | Low | High | High |
| 9 | Operability | Low | High | Moderate | High |

time consumption and operational risk. This comparison aids in selecting suitable RS platforms for specific agricultural tasks based on operational priorities and constraints.

### 1.2 Applications of RS in PA

RS technology has revolutionized PA through its diverse applications, enhancing productivity and sustainability [25]. Crop health monitoring is significantly improved via the analysis of vegetation indices, such as the normalized difference vegetation index (NDVI), which detects chlorophyll levels to assess plant health and stress factors, allowing for early intervention before visible symptoms occur. Additionally, RS facilitates soil analysis and mapping, providing insights into soil characteristics like moisture content and organic matter through microwave and multispectral data, enabling targeted interventions for soil improvement [10]. In water management, thermal infrared and multispectral data optimize irrigation practices by identifying areas that require attention, crucial for water-scarce regions. Furthermore, RS contributes to yield prediction by analyzing vegetative growth stages and biomass and integrating satellite or UAV-derived data into ML models to enhance planning and market strategies. The technology also aids in pest and disease detection through hyperspectral and multispectral sensors that identify early signs of crop distress due to pests or pathogens, facilitating targeted treatment applications that reduce chemical use. Lastly, RS supports precision fertilization by assessing crop nutrient levels, allowing for variable-rate fertilizer applications that minimize waste and environmental impact while improving crop nutrition. These applications demonstrate RS's transformative potential in modern agricultural practices.

Figure 1 illustrates the primary applications of RS in PA, highlighting critical functions such as crop health monitoring, soil analysis, water management, yield prediction, pest and disease detection, and precision fertilization. By leveraging advanced sensors and data analytics, RS technology enables targeted interventions that improve crop productivity, optimize resource use, and enhance sustainability in farming practices.

## 2 UAVs in PA

UAVs are classified into several categories based on their design, flight capabilities, and operational applications in PA [14]. Figure 3 illustrates the classification of UAVs in PA, categorizing them by types such as fixed-wing, single-rotor, multirotor, and hybrid

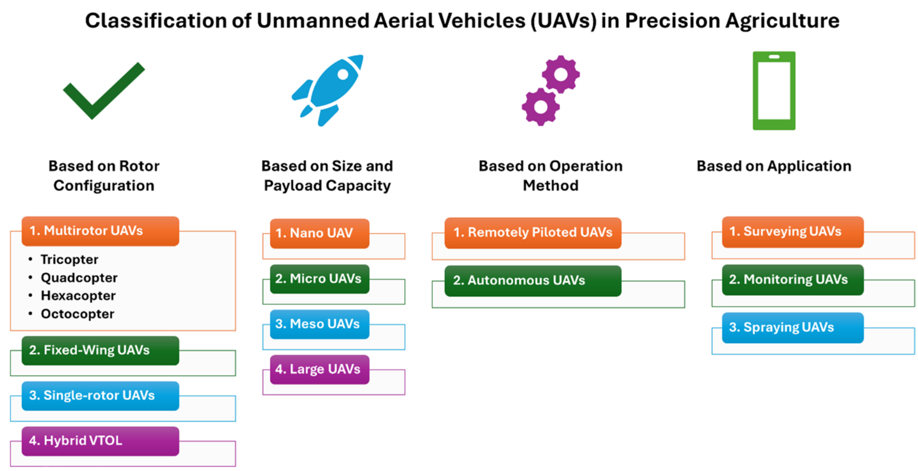


**Fig. 3** Classification of UAV in PA [2, 10]

Vertical Take-off and Landing VTOL. Each UAV type supports specific agricultural applications based on its unique capabilities, such as flight endurance, payload capacity, and maneuverability [17].

UAVs are classified into four primary types based on their design, flight capabilities, and operational characteristics: fixed-wing, single-rotor, multirotor, and hybrid VTOL [2, 14]. Fixed-wing UAVs resemble traditional airplanes with wing structures that generate lift through forward motion. These drones typically require a runway or a catapult for take-off and landing, allowing them to cover vast areas efficiently due to their aerodynamic design. Their longer flight endurance and higher speeds make them ideal for broad area surveys, topographic mapping, and monitoring large crop fields for health and growth patterns. However, they have limited maneuverability, cannot hover, and necessitate a significant amount of space for operation [26]. Single-rotor UAVs, akin to helicopters, feature one large rotor and sometimes a smaller tail rotor for stability. Their ability to take off and land vertically grants them versatility in areas with confined spaces. These UAVs boast longer flight times and higher payload capacities compared to multirotor, making them suitable for carrying heavier sensors, such as LiDAR for detailed soil scanning and terrain mapping in hard-to-reach locations [27]. However, they are more complex to operate, requiring skilled pilots, and are generally more expensive and mechanically intricate than multirotor options [14, 26]. Multirotor UAVs are characterized by multiple rotors, with quadcopters being the most common type. Their VTOL capability allows them to operate effectively in confined spaces, providing high maneuverability and ease of control, which makes them accessible to non-professional operators. They are cost-effective and ideal for close-range crop health monitoring, plant stress detection, and multispectral imaging for PA tasks. However, they have shorter flight times due to battery limitations and lower payload capacities, which restrict their utility in carrying heavy sensors [28]. Finally, Hybrid VTOL UAVs combine the advantages of both fixed-wing and multirotor designs, enabling them to take off and land vertically while transitioning to fixed-wing flight for longer endurance once airborne. This dual capability allows them to operate efficiently in confined areas without requiring runways. Their long-range capabilities make them suitable for large-scale crop monitoring, where they can survey extensive fields in a single flight. Despite their advantages, hybrid UAVs are mechanically more complex and typically more expensive due to their advanced designs and components. Collectively, these UAV types offer diverse solutions for PA, addressing various operational needs and environmental conditions [7, 29].

Table 3 compares Fixed-Wing, Single Rotor, Multirotor, and Hybrid VTOL UAVs by parameters like flight time, endurance, cost, and application suitability. Each type offers distinct advantages, from the endurance of Fixed-Wing for mapping to the maneuverability of Multirotor for precision tasks, aiding in selecting the best UAV type for specific agricultural needs.

An alternative classification of UAVs is based on their size and payload capacity. Nano UAVs are small and lightweight, typically weighing less than 2 kg, and are primarily used for localized monitoring and data collection in smaller fields. Micro UAVs, which weigh between 2 and 5 kg, can accommodate additional sensors, enhancing their data collection capabilities. Meso UAVs, ranging from 5 to 25 kg, offer a balance between payload capacity and flight duration, making them versatile for various agricultural applications. In contrast, large UAVs, exceeding 25 kg, can carry heavier payloads, including advanced sensing equipment, and are often employed in large-scale agricultural operations [30]. UAVs can also be categorized based on their operation method. Remotely piloted UAVs are operated by a pilot using a remote control, allowing for real-time monitoring and data collection, although they require active operator involvement. In contrast, autonomous UAVs can execute pre-programmed missions without human intervention, utilizing GPS and onboard sensors to efficiently navigate and gather data for repetitive tasks [31]. Lastly, UAVs are classified according to their applications. Surveying UAVs are designed for high-resolution aerial mapping and topographic surveys, equipped with cameras and LiDAR systems to capture detailed imagery. Monitoring UAVs are outfitted with multispectral and thermal cameras for crop health assessment, enabling the monitoring of vegetation indices and soil moisture levels. Spraying UAVs are specifically designed for agricultural spraying applications, facilitating targeted pesticide and fertilizer applications to optimize resource use. This classification highlights the diverse capabilities of UAVs in enhancing PA practices [2].

### 2.1 Classification of multirotor UAVs

Multirotor UAVs are categorized based on the number of rotors they use for flight, each offering distinct characteristics related to stability, maneuverability, payload capacity,

**Table 3** Comparative analysis of UAV types for agricultural applications [2]

| Parameters | Fixed-wing | Single rotor | Multirotor | Hybrid VTOL |
|---|---|---|---|---|
| No. of rotors | 1 | 1 (1 large, 1 small on tail) | Tricopter (3), Quadcopter (4), Hexacopter (6), Octocopter (8) | 1 |
| Manufacture complexity | Simple | Complex | Complex | Complex |
| Cost | High | High | Low | High |
| Flying time | 2 h (Battery) | 16 h (Gas engine) | 20–30 min | Long-duration |
| Endurance | High | High (Gas powered) | Limited | High |
| Energy | Battery | Gas engine | Battery | Battery/Gas Engine |
| Speed | Fast | Limited | Limited | Fast |
| Applications | Long-distance mapping, surveillance | Aerial scanning, aerial photography | Crop mapping, aerial imaging, pest monitoring | Long-distance mapping, surveying |
| Drawbacks | Not suitable for hovering | Hard to control, dangerous | Limited payload, short endurance | Imperfect for hovering |

and flight endurance. These features make multirotor UAVs highly adaptable for various PA applications [32]. Figure 4 illustrates the four primary types of multirotor UAVs used in PA: (a) Tricopter, (b) Quadcopter, (c) Hexacopter, and (d) Octocopter. The rotor configuration of each type provides unique advantages: tricopters are agile but less stable, quadcopters strike a balance between stability and versatility, while hexacopters and octocopters, with more rotors, deliver enhanced stability and higher payload capacities, making them ideal for more complex agricultural tasks. The choice of UAV type depends on specific operational needs in PA.

#### *2.1.1 Tricopter (three rotors)*

The tricopter operates using three rotors for lift and thrust, with its design incorporating one rear rotor that can be tilted to provide yaw control. This feature compensates for the inherent stability limitations associated with tricopters compared to quadcopters or hexacopters. One of the key benefits of a tricopter is its simple design, which results in fewer components, potentially leading to lower manufacturing costs. This simplicity not only facilitates easier repairs but also enhances the overall efficiency of the UAV [35]. Furthermore, tricopters exhibit good maneuverability, allowing for agile and rapid responses during flight. However, this three-rotor configuration also presents disadvantages, such as reduced stability, particularly in windy conditions [36]. Also, the payload capacity of tricopters is limited, making them suitable primarily for smaller sensors or cameras. In agricultural applications, tricopters are ideal for small-scale farming tasks that require agility and maneuverability, such as crop scouting in confined areas. Their ability to navigate tight spaces enables farmers to conduct detailed assessments of specific crop sections effectively [31].

The literature on tricopter UAVs reveals significant advancements in their design, control strategies, and applications. A study demonstrated that a tricopter UAV with rotary propellers and swept wings achieved superior path-following accuracy using fuzzy logic controllers over PID controllers, enhancing stability and movement control [36].

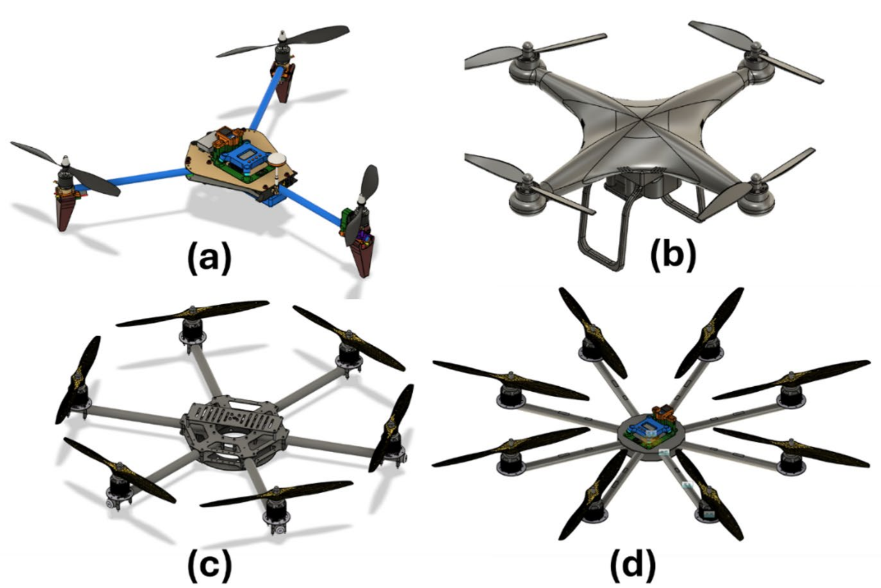


**Fig. 4** Types of Multirotor UAVs: **a** Tricopter; **b** Quadcopter; **c** Hexacopter; **d** Octocopter [33, 34]

Another investigation introduced a hybrid tricopter/flying-wing VTOL UAV, focusing on modular open-source designs and achieving efficient flight with potential for future upgrades such as solar energy systems [35]. Further research proposed a rotor-tilt-free tricopter design that utilized fixed-pitch propellers and rotational speed manipulation, resulting in stable flights with reduced mechanical complexity and lower costs [37]. A different approach employed a tricopter UAV with individually tilted main wings, achieving an 80% improvement in roll rate compared to conventional UAVs through thrust vectoring and dynamic control of wing surfaces [38]. To optimize fuzzy PID controllers for tricopter UAVs, a fusion PSO-EP algorithm was used, yielding rapid response, enhanced precision, and improved stability in nonlinear systems [39]. Another study highlighted the effectiveness of UAVs in agriculture, showcasing their ability to reduce labor costs, improve pesticide application efficiency, and boost crop productivity in developing regions [40]. Lastly, a design for a hybrid tricopter/fixed-wing VTOL drone tailored for post-disaster applications was presented, achieving improved load-carrying capacity and operational stability through a modular carbon fiber structure [41]. Collectively, these studies underscore the diverse capabilities of tricopter UAVs in advancing control systems, operational efficiency, and their application across agriculture, disaster management, and beyond.

#### *2.1.2 Quadcopter (four rotors)*

Quadcopters represent the most prevalent type of multirotor UAV, characterized by four rotors arranged in either an “X” or “+” configuration. This layout enhances stability and ease of control, making quadcopters user-friendly for both novices and experienced operators [42]. Their widespread availability is attributable to a balanced design that offers excellent stability and versatility, allowing them to accommodate various sensors, including RGB cameras, multispectral sensors, and thermal imaging cameras. This adaptability makes quadcopters suitable for diverse agricultural tasks [43]. However, a notable drawback is their limited flight time, typically restricted to 20–30 min due to battery life. While quadcopters can carry lightweight sensors, their capacity for heavier payloads remains moderate. In agriculture, quadcopters are particularly suited for close-range monitoring, crop health assessments, and generating detailed field maps through aerial imaging. Their stability and ease of control enable farmers to collect high-quality data efficiently, facilitating informed decision-making in PA [2, 5].

The literature on quadcopter UAVs highlights their transformative role in modernizing agriculture through precision and efficiency. One study demonstrated the use of an autonomous quadcopter equipped with a multispectral camera for generating terrain mosaics, enabling the monitoring of crop fields and significantly improving ability of farmer to assess vegetation health and optimize agricultural practices [44]. Another analysis provided a comprehensive overview of quadcopters in smart agriculture, emphasizing their advantages in resource optimization, modeling, and their role across various stages of the agricultural cycle, including crop monitoring and resource application [45]. Research focused on designing a lightweight, cost-effective quadcopter system for PA, addressing labor shortages and enhancing rural productivity by automating spraying processes and reducing health risks associated with manual pesticide application [46]. Also, a quadcopter UAV was developed for fertilizer and pesticide spraying, demonstrating its ability to mitigate human exposure to harmful chemicals while effectively targeting inaccessible areas, with the integration of multispectral cameras and universal sprayer modules further improving operational accuracy and efficiency [47]. Collectively, these studies underline the potential of quadcopters in addressing agricultural challenges, including labor shortages, health risks, and inefficiencies, while promoting sustainability and productivity in the sector.

#### 2.1.3 Hexacopter (six rotors)

Hexacopters are advanced multirotor UAVs equipped with six rotors arranged symmetrically, providing additional lift and redundancy, enhancing stability and payload capacity. The six-rotor configuration significantly increases stability, making hexacopters particularly beneficial in windy conditions where maintaining controlled flight is crucial [48]. Furthermore, hexacopters can carry larger and more advanced sensors than quadcopters, including multispectral and hyperspectral cameras. This feature makes them highly valuable for advanced agricultural applications, as they can collect detailed and accurate data necessary for informed decision-making [49]. A key advantage of hexacopters is their redundancy; even if one rotor fails, it can maintain flight, ensuring operational reliability during critical tasks. However, hexacopters do have some drawbacks. Their higher power consumption necessitates more battery power to operate all six rotors, which can lead to shorter flight times compared to quadcopters [50]. Also, the increased complexity and the greater number of motors involved result in higher costs for hexacopter systems. Despite these disadvantages, hexacopters are well-suited for larger agricultural operations that require extended flight times and the ability to carry heavier sensors for tasks such as crop variability mapping and soil analysis. Their enhanced stability and payload capacity render them effective tools for comprehensive agricultural assessments, allowing for more precise and efficient farming practices [32].

Recent advancements in hexacopter UAV technology have demonstrated their potential in diverse applications, including adaptive control, environmental monitoring, collision avoidance, and specialized spraying systems. One study developed an adaptive PID controller using neural networks, achieving enhanced trajectory tracking with minimal control errors, validated through experimental results [51]. Another effort improved the stability and reliability of hexacopters by testing flight parameters and using FEM simulations to optimize performance, particularly under challenging wind conditions [52]. Research on disinfectant spraying showcased a hexacopter capable of carrying a 10 kg payload and operating for 6 min, highlighting its effectiveness in targeted applications during the COVID-19 pandemic [53]. A LiDAR-based collision avoidance system was proposed, which, through Kalman filtering and predictive modeling, reliably maneuvered the UAV around dynamic obstacles, as confirmed by Monte Carlo simulations [54]. Additionally, the combination of a hexacopter UAV with a quadruped robot for forest ecosystem monitoring employed YOLOv5s object detection to achieve cost-effective and near real-time identification of forest health indicators [55]. These studies underscore the versatility and advancements in hexacopter UAV systems, enhancing their capabilities for precision tasks across various domains.

#### 2.1.4 Octocopter (eight rotors)

Octocopters are a sophisticated class of multirotor UAVs that feature eight rotors, providing exceptional stability and enabling them to carry heavy payloads [56]. This configuration makes octocopters particularly suited for specialized, professional-grade applications. The eight-rotor design offers maximum stability, even in adverse weather conditions, ensuring reliability during demanding tasks. These UAVs can accommodate high payload capacities, allowing for the integration of advanced sensors such as LiDAR systems and high-precision imaging equipment [57]. Furthermore, the redundancy inherent in having multiple motors ensures that the octocopter can maintain flight even if one motor fails, enhancing operational safety. However, octocopters exhibit high power consumption, necessitating substantial battery capacity, which can limit flight endurance despite the use of larger batteries. Additionally, the complexity of their design contributes to higher costs, making them a more significant investment compared to simpler multirotor configurations [58]. In agricultural applications, octocopters are particularly advantageous for large-scale operations that require high-resolution imaging, terrain mapping, or the deployment of sophisticated sensors. Their ability to efficiently cover large areas makes them ideal for PA on commercial farms, where accurate data collection is essential for optimization [16].

Advancements in octocopter UAVs have driven innovations in robust control, aerodynamic performance, modeling, and practical applications. A robust adaptive control scheme for a fully actuated octocopter was developed, enabling independent translational and rotational motion for precise trajectory tracking, validated through numerical simulations [59]. Optimization of octocopter aerodynamic efficiency using CFD and experiments resulted in a 71% greater thrust compared to conventional designs [56]. Modeling of an octorotor with a manipulator arm involved kinematic and dynamic analyses with a cascade PID controller, demonstrating effective closed-loop control in simulations [60]. Nonlinear models for radar-equipped octorotors validated PID and linear quadratic controllers for altitude and trajectory tracking, proving their reliability through simulations [61]. Design and simulation of a V-frame octocopter improved payload and roll-pitch stability, utilizing 3D printing for cost-effective manufacturing [62]. These studies highlight octocopter UAVs' potential for enhanced control, efficiency, and diverse applications.

## 3 Summary comparison of multirotor UAVs

Table 4 provides a comparative overview of various multirotor UAV configurations used in agriculture, highlighting their rotor count, operational advantages, limitations, and specialized agricultural applications. Each type, from tricopters to octocopters, offers unique benefits suited to specific tasks, from crop health monitoring to large-scale imaging and precision soil analysis.

**Table 4** Characteristics and applications of multirotor UAVs in agriculture

| Multirotor type | Rotors | Key advantages | Key limitations | Typical agricultural applications |
|---|---|---|---|---|
| Tricopter | 3 | Agile, simple design, easy repair | Lower stability, limited payload | Crop scouting in tight spaces |
| Quadcopter | 4 | Stable, widely available, supports RGB/multispectral cameras | Limited flight time, moderate payload | Crop health assessment, aerial imaging |
| Hexacopter | 6 | High stability, redundancy, supports advanced sensors | High power consumption, costly | Soil analysis, variability mapping |
| Octocopter | 8 | Max stability, high payload capacity, redundant motors | Expensive, complex design | LiDAR mapping, large-scale crop monitoring |

Another classification considers size and payload capacity: nano UAVs are small and lightweight, typically weighing less than 2 kg, used for localized monitoring and data collection in smaller fields; micro UAVs weigh between 2 and 5 kg and can carry additional sensors for enhanced data collection; meso UAVs, ranging from 5 to 25 kg, strike a balance between payload capacity and flight duration, making them versatile for various agricultural applications; and large UAVs, exceeding 25 kg, can carry heavier payloads, including advanced sensing equipment, often employed of large-scale farm operations.

UAVs can also be categorized based on their operation method: remotely piloted UAVs are operated by a pilot using a remote control, allowing for real-time monitoring and data collection but requiring active operator involvement, while autonomous UAVs can execute pre-programmed missions without human intervention, utilizing GPS and onboard sensors to navigate and gather data efficiently for repetitive tasks. Finally, UAVs are classified by their applications: surveying UAVs are designed for high-resolution aerial mapping and topographic surveys, equipped with cameras and LiDAR systems to capture detailed imagery; monitoring UAVs are outfitted with multispectral and thermal cameras for crop health assessment, and monitoring vegetation indices, and soil moisture levels; and spraying UAVs are specifically designed for agricultural spraying applications, enabling targeted pesticide and fertilizer application to optimize resource use. This classification underscores the diverse capabilities of UAVs in enhancing PA practices.

## 4 Technological innovations and AI integration in multirotor UAVs for PA

The rapid advancement of technology has significantly transformed the landscape of PA, particularly through the innovations in multirotor UAVs. These UAVs are now equipped with cutting-edge sensors and sophisticated data analysis capabilities, enabling farmers to monitor crop health, optimize resource usage, and improve agricultural productivity [31]. Figure 5 illustrates key innovations in multirotor UAVs that reshape agricultural practices and enhance farming decision-making processes.

One of the most significant innovations in multirotor UAVs for PA is the integration of advanced sensors, including multispectral, hyperspectral, thermal cameras, LiDAR and RGB sensors. These sophisticated tools provide detailed information on plant health, soil moisture, canopy temperature, and nutrient deficiencies [64]. Notably, hyperspectral imaging has enabled more precise analysis of plant physiological states by capturing data across a wide range of wavelengths, while thermal imaging is instrumental in monitoring plant stress and irrigation efficiency. Furthermore, high-resolution RGB cameras facilitate detailed visual assessments of crop conditions, offering a comprehensive understanding of agricultural dynamics [58].


**Fig. 5** Key technological innovations in multirotor UAVs [31, 63]

Advances in AI and ML have also revolutionized the analysis of UAV-collected data. By applying ML algorithms to aerial imagery, it is now possible to detect patterns related to crop health, predict yield outcomes, and identify disease outbreaks at an early stage [16, 65]. AI-driven image classification methods allow for the precise differentiation between healthy and stressed plants, while deep learning models are increasingly utilized to optimize plant recognition tasks across extensive datasets [66]. These innovations significantly reduce the time and expertise required for farmers to interpret UAV data, thereby enhancing decision-making processes. Also, multirotor UAVs equipped with variable rate technology (VRT) facilitate site-specific management of crops by varying the number of inputs—such as fertilizers, pesticides, or irrigation—applied across a field. Innovations in real-time VRT integration enable UAVs to autonomously adjust input rates in response to field conditions, thereby improving precision and efficiency in agricultural practices. Finally, autonomous flight systems powered by GPS and AI allow multirotor UAVs to follow pre-programmed flight paths and perform complex tasks with minimal human intervention. Swarm technology, which involves multiple UAVs working cooperatively, represents a growing innovation that offers substantial potential for large-scale agricultural monitoring, as swarm UAVs can cover larger areas in shorter timeframes, conducting simultaneous data collection, crop spraying, and field mapping.

### 4.1 Enhancing precision pest management through multirotor UAVs

Multirotor UAVs, or drones, play an increasingly vital role in precision pest management by enhancing the accuracy, efficiency, and sustainability of pest control practices [67]. With advanced sensors, these UAVs can capture high-resolution multispectral, hyperspectral, and thermal imagery, allowing for early detection of pest infestations through indicators like plant stress or chlorophyll reduction. This real-time data enables targeted pesticide applications, reducing chemical use and environmental impact by focusing treatment only on infested areas [16, 68]. Also, the maneuverability of multirotor UAVs allows them to access challenging terrains and densely planted areas, ensuring comprehensive monitoring and treatment. By integrating AI and machine learning, these UAVs can analyse collected data to generate actionable insights on pest patterns, infestation trends, and hotspot identification. The use of UAVs in pest management not only reduces labour costs and health risks for workers but also supports sustainable agriculture by preserving beneficial species and minimizing pesticide exposure to non-target areas [69]. This technology is thus a key contributor to advancing PA by making pest management practices more efficient and environmentally friendly.

Table 5 presents a comprehensive overview of UAV technologies, and their detection techniques used in crop health monitoring. It categorizes various crops, UAV specifications, camera types, targeted pests and diseases, and detection methodologies, along with the algorithms employed and their respective accuracies. This summary highlights the advancements in UAV applications within PA, illustrating their potential to enhance crop management and disease detection.

With ongoing advances in AI-enabled perception, onboard edge computing, and 5G connectivity, multirotor UAVs are poised to play a central role in next-generation smart farming systems. The convergence of UAVs with IoT networks and satellite-aided decision platforms will enhance interoperability and scalability, supporting global food security efforts, especially in climate-vulnerable regions.

**Table 5** Overview of UAV technologies and detection techniques for crop health monitoring

| Sr. No | Crop | No. of Rotor | Camera Type | Pest/Disease Name | Detection Method | Algorithm/Model | Accuracy | Observation | References |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Wheat | 4 | Hyperspectral | Yellow rust | Vegetation indices (VIs), texture features (TFs) | Partial least squares regression (PLSR) | $R^2 = 0.82$ | VI-based model had the highest accuracy in mid-infection; TF-based model effective in mid- and late infection periods | [70] |
| 2 | Olive trees | 6 | Multi-spectral | Xylella fastidiosa | Radiometric and geophysical data fusion | Non-parametric multivariate geostatistics | – | Probabilistic maps created to identify high infection risk areas for preventive action | [71] |
| 3 | Durum wheat | 4 | Thermal, RGB | Fusarium head blight (FHB) | TIR, RGB imaging, ground-based measurements | – | – | Disease detected at mid-stage; UAV imaging allowed FHB detection before significant visible symptoms | [72] |
| 4 | Peach | 4 | RGB | Bacteriosis | CNN and image processing | CNN models | 98.75% | CNN accurately identifies bacterial spots with high speed and potential for UAV integration in field conditions | [73] |
| 5 | Sugar Beet | 4 | RGB | Cercospora leaf spot (CLS) | RGB imagery, CNN | Fully convolutional neural network | High sensitivity | Effective segmentation of CLS symptoms without the need for hyperspectral sensors | [74] |
| 6 | Chinese pine | 4 | Hyperspectral | Pine wilt disease (PWD) | UAV-based hyperspectral imaging | Random forest (RF) | Kappa = 0.58 | UAV imaging combined with VIs and moisture indices effective for detecting early PWD stages | [75] |

**Table 5** (continued)

| Sr. No | Crop | No. of Rotor | Camera Type | Pest/Disease Name | Detection Method | Algorithm/Model | Accuracy | Observation | References |
|---|---|---|---|---|---|---|---|---|---|
| 7 | Chinese pine | 4 | Multispectral | PWD | Multispectral imagery and deep learning | Faster R-CNN, YOLOv4 | 66.7% (Faster R-CNN) | Faster R-CNN had higher accuracy but YOLOv4 was faster; combined models increased early detection rate | [76] |
| 8 | Maize | 6 | Multispectral | Maize streak virus (MSV) | Multispectral RS | Decision trees, linear regression | r = 0.84 | Best predictors included green and red bands at mid-vegetative stages; useful for MSV disease and yield prediction | [77] |
| 9 | Rice | 4 | Imagga Cloud | Rice Pest | IoT-assisted image analysis | AI with Imagga tag confidence | – | Uses IoT and AI for image analysis to identify pests, sends data to cloud, uses confidence values for pest detection, alerts owner for intervention | [68] |
| 10 | Pine | 6 | High-resolution | Pine wilt disease | Object detection | Faster R-CNN, YOLOv3 | 0.602–0.64 (mAP) | YOLOv3 had better speed and smaller model size than Faster R-CNN; effective in predicting infected population under various forest treatments | [78] |
| 11 | Maize | 6 | Convolutional NN | Fall armyworm | Image recognition | VGG16, VGG19, InceptionV3 | 99.92–100% | Models trained with modified images showed high accuracy; corner detection technique enhanced performance of CNN models | [79] |

**Table 5** (continued)

| Sr. No | Crop | No. of Rotor | Camera Type | Pest/Disease Name | Detection Method | Algorithm/Model | Accuracy | Observation | References |
|---|---|---|---|---|---|---|---|---|---|
| 12 | Citrus | 4 | Hyperspectral | Citrus gummosis | Hyperspectral image analysis | F-score for health maps | 0.79 (multispectral), 0.94 (hyperspectral) | Hyperspectral images achieved higher classification accuracy than multispectral, capturing better detail of disease spread | [80] |
| 13 | Rice | 4 | Hyperspectral | Rice false smut | Spectral similarity analysis | Custom spectral and temporal | 74.23% and 85.19% | Hyperspectral bands were identified as sensitive for RFS detection; areas of infection showed expanding trend over time | [81] |
| 14 | Grapevine | 4 | Hyperspectral | Grapevine viral disease | Hyperspectral classification | SVM, RF, 3D-CNN | – | Early asymptomatic detection of grapevine disease using various vegetation indices; 3D-CNN outperformed 2D-CNN in feature extraction | [82] |
| 15 | Wheat | Landsat-8 | Satellite imagery | Powdery mildew and aphids | Multi-temporal image analysis | SMOTE-BPNN, BPNN, SVM | > 80% | Integration of growth and environmental parameters improved pest and disease discrimination; SMOTE-BPNN achieved highest G-means | [83] |
| 16 | Pine | 6 | Multispectral | Pine wood nematode | Multi-spectral analysis | SCANet | 79% | SCANet model enhanced feature extraction and achieved higher precision and recall than other deep learning methods for nematode detection | [84] |

**Table 5** (continued)

| Sr. No | Crop | No. of Rotor | Camera Type | Pest/Disease Name | Detection Method | Algorithm/Model | Accuracy | Observation | References |
|---|---|---|---|---|---|---|---|---|---|
| 17 | Wheat | 4 | Spectral/Texture | Fusarium Head Blight | Spectral and texture features | Logistic model with GLCM | 0.90 accuracy | GLCM texture feature extraction using optimal window sizes improved detection accuracy, with models achieving best performance at specific window sizes | [85] |
| 18 | Cotton | 4 | Hyperspectral imagery (AVIRIS) | Spider mite (Tetranychus turkestani) | Spectral mixture analysis | – | – | Successfully distinguished mite-infested fields; shading affected results | [86] |
| 19 | Potato | 6 | RGB images | Late blight (Phytophthora infestans) | Deep learning (segmentation and severity quantification) | Deep neural networks | 0.386 (IoU for lesions) | High IoU for background; good correlation with visual scores | [87] |
| 20 | Citrus | 4 | Hyperspectral imagery (UAV) | Huanglongbing (HLB) | Multi-feature fusion with spectral bands | SAE neural network | 99.72% | High accuracy for HLB detection; good classification performance | [88] |
| 21 | Soybean | 4 | RGB images | Various pests | Deep learning (classification with fine-tuning) | Inception-v3, Resnet-50, VGG-16, VGG-19, Xception | 93.82% | Deep learning outperformed traditional methods for pest classification | [89] |
| 22 | Banana | 4 | RGB images | Yellow sigatoka | Machine learning (classification) | SVM, ANN, Minimum Distance | 99.28% | SVM outperformed others in quantifying disease extent | [90] |
| 23 | Vineyards | 4 | RGB images | Jacobiasca lybica pest | Artificial neural network (ANN) and geometric techniques | ANN | – | Successful in mapping pest infestation severity | [91] |
| 24 | Citrus | 4 | Hyperspectral imagery (UAV) | Citrus canker | Hyperspectral imaging and machine learning | RBF, KNN | 94%-100% | RBF classifier outperformed KNN in canker detection | [23] |

**Table 5** (continued)

| Sr. No | Crop | No. of Rotor | Camera Type | Pest/Disease Name | Detection Method | Algorithm/Model | Accuracy | Observation | References |
|---|---|---|---|---|---|---|---|---|---|
| 25 | Vineyards | 4 | Hyperspectral, multispectral, RGB | Phylloxera (grape pest) | Integration of multiple sensor data | Predictive model | – | Improved pest surveillance by integrating UAV and ground data | [92] |
| 26 | Cotton | 4 | Multispectral imagery (UAV) | Spider mite (Tetranychus urticae) | Two-stage classification (SVM+CNN) | SVM, CNN | – | Higher accuracy compared to traditional methods for mite detection | [93] |
| 27 | Sugar beet | 4 | Hyperspectral, multispectral, UAV | Beet cyst nematode (BCN) | Spectral indices, canopy height and temperature | Decision trees, SIs | – | Successful in classifying nematode-tolerant and susceptible cultivars | [94] |
| 28 | Potato | 6 | Multispectral imagery | Colorado potato beetle (CPB) | Object-based image analysis (NDVI, height) | – | – | Object-based analysis correlated well with visible CPB damage | [95] |
| 29 | Canola | 8 | Hyperspectral camera | Green peach aphid (Hemiptera: Aphididae) | UAV multispectral images and hyperspectral imaging | – | 72–100% | Potassium deficiency in canola increases susceptibility to aphids. UAV imagery with high resolution showed better classification accuracy than airborne or benchtop images | [96] |

## 5 Challenges in implementing multirotor UAVs in PA

Multirotor UAVs face several challenges that can impede their effective implementation in PA. One of the most significant hurdles is their limited flight time, which generally ranges from 20 to 45 min depending on payload weight and environmental conditions [97]. This constraint restricts the area that can be effectively covered in a single flight, making frequent recharging or battery replacements necessary, especially on larger farms. For example, a DJI Phantom 4 Pro with an average flight time of approximately 30 min and a survey speed of 10 m/s can cover about 18 hectares per flight under optimal conditions [98, 99]. For farms spanning hundreds of hectares, multiple flights are needed, increasing operational downtime and labor costs, which can hinder routine monitoring and timely interventions. Additionally, the payload capacity of these UAVs often limits the number and type of sensors that can be deployed simultaneously, which affects the comprehensiveness of data collection during aerial surveys. This limitation can reduce the precision of agricultural assessments, particularly in diverse crop environments requiring multispectral or hyperspectral imaging [100].

Regulatory restrictions pose a considerable barrier to widespread UAV use in agriculture. Many countries enforce strict aviation regulations governing UAV operations, including limitations on flight altitudes, requirements for line-of-sight (LOS) operations, and certification mandates for UAV pilots [101, 102]. In practice, these regulations often prohibit beyond visual line-of-sight (BVLOS) flights without special permissions, significantly limiting UAV efficiency in large-scale farming. For instance, studies have shown that such restrictions can increase operational complexity by 30–50%, slowing adoption rates and constraining UAV utility in expansive agricultural landscapes [103]. In the United States and Europe, this has resulted in limited BVLOS permissions, affecting scalability of UAV deployments [104].

In Punjab, India, UAVs improved crop health monitoring accuracy by approximately 25%, yet the short flight duration and regulatory constraints limited survey frequency to once per week instead of the ideal daily monitoring, thereby reducing the potential yield benefits [105]. In the U.S. Midwest, the high initial investment—including UAV hardware, sensors, and training costs averaging $15,000 per system—posed adoption barriers for small to medium farms, despite clear evidence of productivity gains [106]. The processing and management of large volumes of data generated by UAVs also present significant challenges. A single UAV flight capturing multispectral imagery can generate upwards of 50 GB of raw data per hectare, demanding robust data storage, specialized software, and high-performance computing resources for timely analysis. These requirements add further operational complexity and costs, particularly for farms lacking advanced IT infrastructure [107]. Finally, access to UAV technology is limited in regions with inadequate infrastructure, such as unreliable internet connectivity and GPS signal availability, which are essential for effective UAV operation and real-time data transmission.

### 5.1 Security challenges and solutions in UAV systems

UAVs face multiple security threats that can compromise their operation and the integrity of collected data. The common attack types include GPS spoofing and jamming, where attackers manipulate or block GPS signals to disrupt UAV navigation, potentially causing loss of control or mission failure. Also, communication interception and data theft pose risks as UAVs often transmit sensitive information wirelessly, which can be intercepted by unauthorized entities. UAV systems are also vulnerable to malware and software exploits, where attackers infiltrate control systems to hijack UAVs or induce malfunction [108].

To mitigate these threats, several solutions have been developed. The use of encrypted communication protocols protects data transmissions against interception and tampering. Implementing anti-jamming technologies and combining GPS with other sensors (e.g., inertial measurement units) increases navigation robustness against signal interference. Regular software updates and intrusion detection systems enhance defense against malware and unauthorized access, ensuring UAV control software remains secure [109]. Together, these measures contribute to improving the reliability and safety of UAV operations in various applications.

## 6 Future prospects

The future of multirotor UAVs in PA is promising, particularly with advancements in battery and energy innovations. The development of more efficient battery technologies is critical for overcoming the flight time limitations that currently hinder UAV operations. Research into solar-powered UAVs and the utilization of fuel cells presents exciting opportunities to extend flight durations significantly. Additionally, the implementation of wireless charging systems and the establishment of in-field charging stations could enhance operational efficiency by minimizing downtime between flights, thereby allowing for more extensive data collection and monitoring throughout the day. These innovations will likely facilitate the deployment of UAVs over larger areas, improving their effectiveness in agricultural applications.

Moreover, the integration of multirotor UAVs with the IoT and big data platforms stands to revolutionize PA. By equipping UAVs with IoT-enabled sensors, real-time data can be communicated to ground-based systems for immediate analysis using big data analytics tools. This integration fosters the creation of more accurate predictive models concerning crop yield, disease spread, and soil health, thereby allowing for real-time adjustments to farming practices, such as optimized irrigation and fertilization strategies based on evolving field conditions [110]. Additionally, advancements in swarm technologies will enable multiple UAVs to operate in concert, performing coordinated tasks more efficiently. As AI and communication technologies advance, these UAV swarms can autonomously share data and make collective decisions, executing complex tasks such as simultaneous multispectral scanning and real-time crop spraying over vast agricultural expanses. The synergy between UAVs and AI-driven decision support systems (DSS) will further empower farmers by providing them with informed insights based on real-time data, leading to precise input management and ultimately higher crop yields [111].

Despite these promising applications, the integration of IoT in PA also presents challenges, including data interoperability across different devices, ensuring security and privacy of transmitted data, scalability of IoT networks to cover large agricultural fields, and power management for IoT sensors. Solutions to these issues involve adopting standardized communication protocols such as MQTT or CoAP to ensure seamless data exchange, implementing strong security frameworks (encryption and authentication), utilizing edge computing for real-time data processing and reduced cloud dependency, and employing energy-efficient sensor designs with power-saving modes. These strategies will help overcome integration barriers, ensuring that IoT-powered UAV systems can operate reliably and securely, ultimately enhancing the effectiveness of PA practices [112].

To fully unlock the potential of AI, IoT, and swarm UAVs in PA, several critical technological gaps must be addressed through focused research. Enhancing energy efficiency and extending flight duration remain paramount, as current battery technologies still limit UAV operational time. Advancements in higher-capacity batteries, integration of renewable energy sources such as solar cells, and development of wireless in-field charging systems are essential to enable longer, uninterrupted UAV missions. Improving IoT network interoperability and scalability is also crucial, given the diversity of sensors and UAV platforms used in agriculture [113]. The adoption of standardized communication protocols like MQTT and CoAP, coupled with scalable network architectures, will ensure seamless and reliable data exchange across expansive farming areas. Furthermore, advancing autonomous swarm UAV coordination requires robust algorithms for distributed task allocation, real-time communication, and fault tolerance, supported by low-latency protocols to synchronize multiple UAVs effectively. Cybersecurity and data privacy must be strengthened to protect UAV operations against threats such as GPS spoofing and data interception, emphasizing the need for secure communication frameworks, encryption techniques, and intrusion detection systems [114]. Lastly, the development of explainable and computationally efficient AI models tailored for edge computing will facilitate transparent, rapid decision-making, fostering greater trust and practical adoption among farmers. Addressing these challenges will be critical in realizing the full capabilities of UAV technologies in PA.

## 7 The economic potential of UAV-driven agricultural innovations

The integration of UAV-based RS technology in agriculture holds significant economic potential by enhancing productivity and sustainability on a global scale. Regions such as South and Southeast Asia, Western and Central Europe, Central America and the Caribbean, and Southern Africa stand to benefit greatly from UAV adoption, as it enables farmers to optimize crop management, monitor plant health more accurately, and make data-driven decisions. These practices can directly contribute to meeting the increasing demands of a growing global population [115]. Recent cost–benefit analyses have highlighted that UAV-based PA practices can reduce input costs—including fertilizers, pesticides, and irrigation—by approximately 15–30% due to more precise resource management. In the U.S., large-scale farming operations have demonstrated a net return on investment (ROI) of 20–35%, with a payback period of 2–3 years, depending on farm size and crop type [116, 117]. These findings underscore the substantial economic advantages of UAV implementation in well-resourced agricultural systems.

However, the situation in developing regions, such as India and parts of Sub-Saharan Africa, presents additional challenges. High initial investment costs—ranging from $10,000 to $20,000 per UAV system—pose a significant barrier for smallholder farmers. Moreover, annual recurring costs for maintenance, data processing, and operator training average around $2,000–$4,000 per UAV system, further influencing adoption rates in resource-constrained settings. Limited access to financing and inadequate technical training exacerbate these barriers, slowing the widespread adoption of UAV technology [17, 19]. Despite these obstacles, UAV deployment has demonstrated the potential to significantly enhance agricultural productivity in developing regions. Studies have shown that PA enabled by UAVs can increase crop yields by 10–20%, leading to notable economic gains for farmers. For instance, pilot projects conducted in Punjab, India, reported that UAV-assisted crop monitoring and data analysis improved net farm profits by up to 12% within a single growing season [111]. In addition to direct farm-level benefits, broader economic impacts include increased agricultural exports, enhanced food security, and the creation of new employment opportunities in UAV operations, maintenance, and data analytics [118]. These developments contribute to poverty alleviation and bolster the economic resilience of rural communities. Taking everything into account, while the economic potential of UAV-driven innovations in agriculture is clear, addressing the adoption barriers in developing regions—such as initial investment costs and technical support—will be crucial for realizing these benefits on a broader scale.

## 8 Conclusion

Multirotor UAVs are poised to significantly transform PA by enabling accurate monitoring, analysis, and management of crops and resources. Through advanced sensor technologies, AI, and ML, these UAVs facilitate tasks such as crop health monitoring and variable-rate applications, promoting resource efficiency and sustainability. Despite challenges related to flight duration, payload capacity, regulations, and data processing, ongoing advancements—particularly in battery technologies, IoT integration, and swarm UAV operations—are expected to enhance their capabilities and adoption. The economic potential of UAV-based solutions is substantial, offering opportunities to improve agricultural productivity, boost food security, and foster economic growth, especially in developing regions. Also, as UAV technology matures and becomes more accessible, it will likely democratize PA, making advanced monitoring and management tools available to smallholder and resource-constrained farmers. The integration of UAVs with decision support systems and real-time data analytics will empower farmers to make timely, data-driven decisions, leading to more resilient and profitable farming practices. As a final note, the multirotor UAVs represent a critical tool for modern, data-driven, and sustainable agricultural practices. Their adoption is expected to play a pivotal role in addressing the global challenges of food security and climate change, shaping the future of farming for generations to come.

**Abbreviations**

| | |
|---|---|
| AI | Artificial intelligence |
| BVLOS | Beyond visual line of sight |
| CNN | Convolutional neural network |
| CoAP | Constrained application protocol |
| CPB | Citrus peel borer |
| DSS | Decision support system |
| FHB | Fusarium head blight |
| HLB | Huanglongbing (citrus greening disease) |
| IoT | Internet of things |
| ML | Machine learning |
| MSV | Maize streak virus |
| MQTT | Message queuing telemetry transport |
| NDVI | Normalized difference vegetation index |
| PA | Precision agriculture |
| PWD | Pine wilt disease |
| R-CNN | Region-based convolutional neural network |
| RS | Remote sensing |
| ROI | Return on investment |
| TFs | Texture features |
| UAVs | Unmanned aerial vehicles |
| VIs | Vegetation indices |
| VRT | Variable rate technology |
| VTOL | Vertical take-off and landing |

**Author contributions**

Sanket S. Unde wrote the original draft and contributed to investigation and data curation. V. K. Kurkute and Sachin S. Chavan supervised the study and contributed to conceptualization. Dadaso D. Mohite contributed to writing—reviewing and editing, data curation, and methodology. Akshay A. Harale and Ayaan Chougle contributed to data curation and software. All authors reviewed the manuscript.

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**Data availability**

Data is provided within the manuscript.

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**References**

1. Gupta G, Pal SK. Applications of AI in precision agriculture. Discov Agric. 2025;3(1):61. https://doi.org/10.1007/s44279-025-00220-9.
2. Velusamy P, Rajendran S, Mahendran RK, Naseer S, Shafiq M, Choi J-G. Unmanned aerial vehicles (UAV) in precision agriculture: applications and challenges. Energies. 2021;15(1):217. https://doi.org/10.3390/en15010217.
3. Mohite DD, Chavan SS, Jadhav VS, Kanase T, Kadam MA, Singh AS. Vermicomposting: a holistic approach for sustainable crop production, nutrient-rich bio fertilizer, and environmental restoration. Discov Sustain. 2024. https://doi.org/10.1007/s43621-024-00245-y.
4. Kadam SA, Kadam PS, Mohite DD. Design and experimental analysis of a closed-loop autonomous rotary hydroponics system for revolutionizing fenugreek yield and enhancing food security. Discov Sustain. 2024;5(1):137. https://doi.org/10.1007/s43621-024-00339-7.
5. Laghari AA, Jumani AK, Laghari RA, Nawaz H. Unmanned aerial vehicles: a review. Cognitive Robotics. 2023;3:8–22. https://doi.org/10.1016/j.cogr.2022.12.004.
6. Meesaragandla S, Jagtap MP, Khatri N, Madan H, Vadduri AA. Herbicide spraying and weed identification using drone technology in modern farms: a comprehensive review. Results Eng. 2024;21:101870. https://doi.org/10.1016/j.rineng.2024.101870.
7. Rachmawati TSN, Kim S. Unmanned aerial vehicles (UAV) integration with digital technologies toward construction 4.0: a systematic literature review. Sustainability. 2022;14(9):5708. https://doi.org/10.3390/su14095708.
8. Ahmed F, Mohanta JC, Keshari A, Yadav PS. Recent advances in unmanned aerial vehicles: a review. Arab J Sci Eng. 2022;47(7):7963–84. https://doi.org/10.1007/s13369-022-06738-0.
9. Outay F, Mengash HA, Adnan M. Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: recent advances and challenges. Transp Res Part A Policy Pract. 2020;141:116–29. https://doi.org/10.1016/j.tra.2020.09.018.
10. Tahir MN, Lan Y, Zhang Y, Wenjiang H, Wang Y, Naqvi SMZA. Application of unmanned aerial vehicles in precision agriculture. In: Precision agriculture, Elsevier; 2023. pp. 55–70. https://doi.org/10.1016/B978-0-443-18953-1.00001-5.
11. Khan S, Mazhar T, Shahzad T, Khan MA, Guizani S, Hamam H. Future of sustainable farming: exploring opportunities and overcoming barriers in drone-IoT integration. Discov Sustain. 2024;5(1):470. https://doi.org/10.1007/s43621-024-00736-y.
12. Grando L, Jaramillo JFG, Leite JRE, Ursini EL. Systematic literature review methodology for drone recharging processes in agriculture and disaster management. Drones. 2025;9(1):40. https://doi.org/10.3390/drones9010040.
13. Shah SFA, et al. Applications, challenges, and solutions of unmanned aerial vehicles in smart city using blockchain. PeerJ Comput Sci. 2024;10:e1776. https://doi.org/10.7717/peerj-cs.1776.
14. Al-Shareeda MA, Saare MA, Manickam S. Unmanned aerial vehicle: a review and future directions. IJEECS. 2023;30(2):778–86. https://doi.org/10.11591/ijeecs.v30.i2.pp778-786.
15. Mowla MN, Asadi D, Durhasan T, Jafari JR, Amoozgar M. Recent advancements in morphing applications: architecture, artificial intelligence integration, challenges, and future trends-a comprehensive survey. Aerosp Sci Technol. 2025;161:110102. https://doi.org/10.1016/j.ast.2025.110102.
16. Tsouros DC, Bibi S, Sarigiannidis PG. A review on UAV-based applications for precision agriculture. Information. 2019;10(11):349. https://doi.org/10.3390/info10110349.
17. Raj M, B HN, Gupta S, Atiquzzaman M, Rawlley O, Goel L. Leveraging precision agriculture techniques using UAVs and emerging disruptive technologies. Energy Nexus. 2024;14:100300. https://doi.org/10.1016/j.nexus.2024.100300.
18. Zhang Z, Zhu L. A review on unmanned aerial vehicle remote sensing: platforms, sensors, data processing methods, and applications. Drones. 2023;7(6):398. https://doi.org/10.3390/drones7060398.
19. Makam S, Komatineni BK, Meena SS, Meena U. Unmanned aerial vehicles (UAVs): an adoptable technology for precise and smart farming. Discov Internet Things. 2024;4(1):12. https://doi.org/10.1007/s43926-024-00066-5.
20. Arumai Ruban J, Santhoshkumar S, Mohamed AT, Amalraj JJ, Lakshmi RB. Automated crop health monitoring and drone-based image processing for crop disease detection in smart farming using IoT. JISEM. 2025;10(45s):1280–97. https://doi.org/10.52783/jisem.v10i45s.9154.
21. Lyu X, Li X, Dang D, Dou H, Wang K, Lou A. Unmanned aerial vehicle (UAV) remote sensing in grassland ecosystem monitoring: a systematic review. Remote Sens. 2022;14(5):1096. https://doi.org/10.3390/rs14051096.
22. Ranjan C, Srinivas J, Balaji PS, Kumar K. Precision agriculture: leveraging artificial intelligence and drones for eco-friendly farming. In: Advances in environmental engineering and green technologies, M. U. Tariq and R. P. Sergio, Eds., IGI Global, 2025. pp. 175–212. https://doi.org/10.4018/979-8-3693-7483-2.ch007.
23. Abdulridha J, Batuman O, Ampatzidis Y. UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning. Remote Sens. 2019;11(11):1373. https://doi.org/10.3390/rs11111373.
24. Sishodia RP, Ray RL, Singh SK. Applications of remote sensing in precision agriculture: a review. Remote Sens. 2020;12(19):3136. https://doi.org/10.3390/rs12193136.
25. Triantafyllou A, Sarigiannidis P, Bibi S. Precision agriculture: a remote sensing monitoring system architecture. Information. 2019;10(11):348. https://doi.org/10.3390/info10110348.
26. Mohsan SAH, Khan MA, Noor F, Ullah I, Alsharif MH. Towards the unmanned aerial vehicles (UAVs): a comprehensive review. Drones. 2022;6(6):147. https://doi.org/10.3390/drones6060147.

27. Chen X, et al. A calculation method for cotton phenotypic traits based on unmanned aerial vehicle LiDAR combined with a three-dimensional deep neural network. Comput Electron Agric. 2025;230:109857. https://doi.org/10.1016/j.compag.2024.109857.
28. Vaigandla KK, Thatipamula S, Karne RK. Investigation on unmanned aerial vehicle (UAV): an overview. JSWS. 2022;4(3):130–48. https://doi.org/10.36548/jsws.2022.3.001.
29. Telli K, et al. A comprehensive review of recent research trends on unmanned aerial vehicles (UAVs). Systems. 2023;11(8):400. https://doi.org/10.3390/systems11080400.
30. Ps R, Jeyan ML. Mini unmanned aerial systems (UAV)—a review of the parameters for classification of a mini UAV. IJAAA. 2020. https://doi.org/10.15394/ijaaa.2020.1503.
31. Mohsan SAH, Othman NQH, Li Y, Alsharif MH, Khan MA. Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends. Intel Serv Robotics. 2023. https://doi.org/10.1007/s11370-022-00452-4.
32. Mukherjee A, Misra S, Raghuwanshi NS. A survey of unmanned aerial sensing solutions in precision agriculture. J Netw Comput Appl. 2019;148:102461. https://doi.org/10.1016/j.jnca.2019.102461.
33. Shahi TB, Xu C-Y, Neupane A, Guo W. Recent advances in crop disease detection using UAV and deep learning techniques. Remote Sens. 2023;15(9):2450. https://doi.org/10.3390/rs15092450.
34. Cai G, Dias J, Seneviratne L. A survey of small-scale unmanned aerial vehicles: recent advances and future development trends. Un Sys. 2014;02(02):175–99. https://doi.org/10.1142/S2301385014300017.
35. Carlson S. A hybrid tricopter/flying-wing VTOL UAV. In: 52nd aerospace sciences meeting, National Harbor, Maryland: American Institute of Aeronautics and Astronautics; 2014. https://doi.org/10.2514/6.2014-0016.
36. Jatsun S, Emelyanova O, Martinez Leon AS, Stykanyova S. Control fligth of a UAV type tricopter with fuzzy logic controller. In: 2017 dynamics of systems, mechanisms and machines (dynamics), Omsk: IEEE; 2017. pp. 1–5. https://doi.org/10.1109/Dynamics.2017.8239459.
37 Sababha BH, Zu HMA, Bi NA, Rawashdeh OA. A rotor-tilt-free tricopter UAV: design, modelling, and stability control. IJMA. 2015;5(2–3):107. https://doi.org/10.1504/IJMA.2015.075956.
38. Nam K-J, Joung J, Har D. Tri-copter UAV with individually tilted main wings for flight maneuvers. IEEE Access. 2020;8:46753–72. https://doi.org/10.1109/ACCESS.2020.2978578.
39. Tran HK, Chiou J-S, Dang V-H. New fusion algorithm-reinforced pilot control for an agricultural tricopter UAV. Mathematics. 2020;8(9):1499. https://doi.org/10.3390/math8091499.
40. Rahman MFF, Fan S, Zhang Y, Chen L. A comparative study on application of unmanned aerial vehicle systems in agriculture. Agriculture (Basel). 2021;11(1):22. https://doi.org/10.3390/agriculture11010022.
41. Baldovino RG, Laurel KEY. Design and development of a tri-copter/fixed-wing VTOL drone for post-disaster applications. In: 2024 9th international conference on mechatronics engineering (ICOM), Kuala Lumpur, Malaysia: IEEE; 2024. pp. 423–428. https://doi.org/10.1109/ICOM61675.2024.10652407.
42. Bashi OID, Hasan WZW, Azis N, Shafie S, Wagatsuma H. Unmanned aerial vehicle quadcopter: a review. J Comput Theor Nanosci. 2017;14(12):5663–75. https://doi.org/10.1166/jctn.2017.7049.
43. Wang P, Man Z, Cao Z, Zheng J, Zhao Y. Dynamics modelling and linear control of quadcopter. In: 2016 international conference on advanced mechatronic systems (ICAMechS), Melbourne, Australia: IEEE; 2016. pp. 498–503. https://doi.org/10.1109/ICAMechS.2016.7813499.
44. Navia J, Mondragon I, Patino D, Colorado J. Multispectral mapping in agriculture: terrain mosaic using an autonomous quadcopter UAV. In: 2016 international conference on unmanned aircraft systems (ICUAS), Arlington: IEEE; 2016. pp. 1351–1358. https://doi.org/10.1109/ICUAS.2016.7502606.
45. Karam K, Mansour A, Khaldi M, Clement B, Ammad-Uddin M. Quadcopters in smart agriculture: applications and modelling. Appl Sci. 2024;14(19):9132. https://doi.org/10.3390/app14199132.
46. Kabra TS, Kardile AV, Deeksha MG, Mane DB, Bhosale PR, Belekar AM. Design, development and optimization of a quadcopter for agricultural applications. Int Res J Eng Technol. 2017;4(7):1632–6.
47. Meivel S, Maguteeswaran R, Gandhiraj N, Srinivasan G. Quadcopter UAV based fertilizer and pesticide spraying system. Int Acad Res J Eng Sci. 2016;1(1):8–12.
48. Liu P, et al. A review of rotorcraft unmanned aerial vehicle (UAV) developments and applications in civil engineering. Smart Struct Syst. 2014;13(6):1065–94. https://doi.org/10.12989/SSS.2014.13.6.1065.
49. Senthilkumar S, et al. Design, dynamics, development and deployment of hexacopter for agricultural applications. In: 2021 international conference on advancements in electrical, electronics, communication, computing and automation (ICAECA), Coimbatore, India: IEEE; 2021, pp. 1–6. https://doi.org/10.1109/ICAECA52838.2021.9675753.
50. Suprapto BY, Heryanto MA, Suprijono H, Muliadi J, Kusumoputro B. Design and development of heavy-lift hexacopter for heavy payload. In: 2017 international seminar on application for technology of information and communication (iSemantic), Semarang: IEEE; 2017. pp. 242–247. https://doi.org/10.1109/ISEMANTIC.2017.8251877.
51. Rosales C, Soria CM, Rossomando FG. Identification and adaptive PID control of a hexacopter UAV based on neural networks. Adapt Control Signal. 2019;33(1):74–91. https://doi.org/10.1002/acs.2955.
52. Stamate M-A, Pupăză C, Nicolescu F-A, Moldoveanu C-E. Improvement of hexacopter UAVs attitude parameters employing control and decision support systems. Sensors (Basel). 2023;23(3):1446. https://doi.org/10.3390/s23031446.
53. Arief UM, et al. Design of hexacopter UAV system for disinfectant spraying. IOP Conf Ser Earth Environ Sci. 2021;700(1):012023. https://doi.org/10.1088/1755-1315/700/1/012023.
54. Park J, Cho N. Collision avoidance of hexacopter UAV based on LiDAR data in dynamic environment. Remote Sens. 2020;12(6):975. https://doi.org/10.3390/rs12060975.
55. Idrissi M, et al. Evaluating the forest ecosystem through a semi-autonomous quadruped robot and a hexacopter UAV. Sensors (Basel). 2022;22(15):5497. https://doi.org/10.3390/s22155497.
56. Zhu H, Nie H, Zhang L, Wei X, Zhang M. Design and assessment of octocopter drones with improved aerodynamic efficiency and performance. Aerosp Sci Technol. 2020;106:106206. https://doi.org/10.1016/j.ast.2020.106206.
57. Li W, Wu B. Computational fluid dynamics investigation of aerodynamics for agricultural drones. Comput Electron Agric. 2024;227:109528. https://doi.org/10.1016/j.compag.2024.109528.
58. Deng L, Mao Z, Li X, Hu Z, Duan F, Yan Y. UAV-based multispectral remote sensing for precision agriculture: a comparison between different cameras. ISPRS J Photogramm Remote Sens. 2018;146:124–36. https://doi.org/10.1016/j.isprsjprs.2018.09.008.

59. Shu P, Li F, Zhao J, Oya M. Robust adaptive control for a novel fully-actuated octocopter UAV with wind disturbance. J Intell Robot Syst. 2021;103(1):6. https://doi.org/10.1007/s10846-021-01450-x.
60. Ollervides-Vazquez EJ, Tellez-Belkotosky PA, Santibañez V, Rojo-Rodriguez EG, Reyes-Osorio LA, Garcia-Salazar O. Modeling and simulation of an octorotor UAV with manipulator arm. Drones. 2023;7(3):168. https://doi.org/10.3390/drones7030168.
61. Makarov M, et al. Octorotor UAVs for radar applications: modeling and analysis for control design. In: 2015 workshop on research, education and development of unmanned aerial systems (RED-UAS), Cancun: IEEE; 2015, pp. 288–297. https://doi.org/10.1109/RED-UAS.2015.7441019.
62. Minh TB, Vo H, Hua LT. Development of a novel V-frame octocopter: design, kinematic analysis and simulation using PID controllers with Ziegler Nichols tuning method. IJIUS. 2023;11(3):320–40. https://doi.org/10.1108/IJIUS-08-2021-0087.
63. Barcelos CO, Fagundes-Júnior LA, Mendes ALC, Gandolfo DC, Brandão AS. Integration of payload sensors to enhance UAV-based spraying. Drones. 2024;8(9):490. https://doi.org/10.3390/drones8090490.
64. Aragon RV, Rocha Castano C, Correa AC. Impact and technological innovation of UAS/drones in the world economy : VI international conference on innovation and trends in engineering (CONIITI 2020). In: 2020 congreso internacional de innovación y tendencias en ingeniería (CONIITI), Bogotá: IEEE; 2020, pp. 1–4. https://doi.org/10.1109/CONIITI51147.2020.9240228.
65. Anam I, Arafat N, Hafiz MS, Jim JR, Kabir MM, Mridha MF. A systematic review of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture. Smart Agric Technol. 2024;9:100647. https://doi.org/10.1016/j.atech.2024.100647.
66. Pai DG, Kamath R, Balachandra M. Deep learning techniques for weed detection in agricultural environments: a comprehensive review. IEEE Access. 2024;12:113193–214. https://doi.org/10.1109/ACCESS.2024.3418454.
67. Guebsi R, Mami S, Chokmani K. Drones in precision agriculture: a comprehensive review of applications, technologies, and challenges. Drones. 2024;8(11):686. https://doi.org/10.3390/drones8110686.
68. Bhoi SK, et al. An internet of things assisted unmanned aerial vehicle based artificial intelligence model for rice pest detection. Microprocess Microsyst. 2021;80:103607. https://doi.org/10.1016/j.micpro.2020.103607.
69. Alqurashi FA, Alsolami F, Abdel-Khalek S, Sayed Ali E, Saeed RA. Machine learning techniques in internet of UAVs for smart cities applications. IFS. 2022;42(4):3203–26. https://doi.org/10.3233/JIFS-211009.
70. Guo A, et al. Wheat yellow rust detection using UAV-based hyperspectral technology. Remote Sens. 2021;13(1):123. https://doi.org/10.3390/rs13010123.
71. Castrignanò A, et al. A geostatistical fusion approach using UAV data for probabilistic estimation of *Xylella fastidiosa* subsp. *pauca* infection in olive trees. Sci Total Environ. 2021;752:141814. https://doi.org/10.1016/j.scitotenv.2020.141814.
72. Francesconi S, Harfouche A, Maesano M, Balestra GM. UAV-based thermal, RGB imaging and gene expression analysis allowed detection of Fusarium head blight and gave new insights into the physiological responses to the disease in Durum wheat. Front Plant Sci. 2021;12:628575. https://doi.org/10.3389/fpls.2021.628575.
73. Yadav S, Sengar N, Singh A, Singh A, Dutta MK. Identification of disease using deep learning and evaluation of bacteriosis in peach leaf. Ecol Informatics. 2021;61:101247. https://doi.org/10.1016/j.ecoinf.2021.101247.
74. Görlich F, Marks E, Mahlein A-K, König K, Lottes P, Stachniss C. Uav-based classification of Cercospora leaf spot using RGB images. Drones. 2021;5(2):34. https://doi.org/10.3390/drones5020034.
75. Yu R, Ren L, Luo Y. Early detection of pine wilt disease in *Pinus tabuliformis* in North China using a field portable spectrometer and UAV-based hyperspectral imagery. Forest Ecosyst. 2021;8:44. https://doi.org/10.1186/s40663-021-00328-6.
76. Yu R, Luo Y, Zhou Q, Zhang X, Wu D, Ren L. Early detection of pine wilt disease using deep learning algorithms and UAV-based multispectral imagery. For Ecol Manage. 2021;497:119493. https://doi.org/10.1016/j.foreco.2021.119493.
77. Chivasa W, Mutanga O, Burgueño J. UAV-based high-throughput phenotyping to increase prediction and selection accuracy in maize varieties under artificial MSV inoculation. Comput Electron Agric. 2021;184:106128. https://doi.org/10.1016/j.compag.2021.106128.
78. Wu B, et al. Application of conventional UAV-based high-throughput object detection to the early diagnosis of pine wilt disease by deep learning. For Ecol Manage. 2021;486:118986. https://doi.org/10.1016/j.foreco.2021.118986.
79. Ishengoma FS, Rai IA, Said RN. Identification of maize leaves infected by fall armyworms using UAV-based imagery and convolutional neural networks. Comput Electron Agric. 2021;184:106124. https://doi.org/10.1016/j.compag.2021.106124.
80. Moriya ÉAS, et al. Detection and mapping of trees infected with citrus gummosis using UAV hyperspectral data. Comput Electron Agric. 2021;188:106298. https://doi.org/10.1016/j.compag.2021.106298.
81. An G, et al. Extraction of areas of rice false smut infection using UAV hyperspectral data. Remote Sens. 2021;13(16):3185. https://doi.org/10.3390/rs13163185.
82. Nguyen C, Sagan V, Maimaitiyiming M, Maimaitijiang M, Bhadra S, Kwasniewski MT. Early detection of plant viral disease using hyperspectral imaging and deep learning. Sensors (Basel). 2021;21(3):742. https://doi.org/10.3390/s21030742.
83. Ma H, et al. Integrating growth and environmental parameters to discriminate powdery mildew and aphid of winter wheat using bi-temporal Landsat-8 imagery. Remote Sens. 2019;11(7):846. https://doi.org/10.3390/rs11070846.
84. Qin J, Wang B, Wu Y, Lu Q, Zhu H. Identifying pine wood nematode disease using UAV images and deep learning algorithms. Remote Sens. 2021;13(2):162. https://doi.org/10.3390/rs13020162.
85. Xiao Y, Dong Y, Huang W, Liu L, Ma H. Wheat fusarium head blight detection using UAV-based spectral and texture features in optimal window size. Remote Sens. 2021;13(13):2437. https://doi.org/10.3390/rs13132437.
86. Fitzgerald GJ, Maas SJ, Detar WR. Spider mite detection and canopy component mapping in cotton using hyperspectral imagery and spectral mixture analysis. Precis Agric. 2004;5(3):275–89. https://doi.org/10.1023/B:PRAG.0000032766.88787.5f.
87. Gao J, Westergaard JC, Sundmark EHR, Bagge M, Liljeroth E, Alexandersson E. Automatic late blight lesion recognition and severity quantification based on field imagery of diverse potato genotypes by deep learning. Knowl-Based Syst. 2021;214:106723. https://doi.org/10.1016/j.knosys.2020.106723.
88. Deng X, et al. Detection of citrus huanglongbing based on multi-input neural network model of UAV hyperspectral remote sensing. Remote Sens. 2020;12(17):2678. https://doi.org/10.3390/rs12172678.
89. Tetila EC, et al. Detection and classification of soybean pests using deep learning with UAV images. Comput Electron Agric. 2020;179:105836. https://doi.org/10.1016/j.compag.2020.105836.
90. Calou VBC, Teixeira ADS, Moreira LCJ, Lima CS, De Oliveira JB, De Oliveira MRR. The use of UAVs in monitoring yellow sigatoka in banana. Biosyst Eng. 2020;193:115–25. https://doi.org/10.1016/j.biosystemseng.2020.02.016.

91. del-Campo-Sanchez A, Ballesteros R, Hernandez-Lopez D, Ortega JF, Moreno MA, and on behalf of Agroforestry and Cartography Precision Research Group. Quantifying the effect of *Jacobiasca lybica* pest on vineyards with UAVs by combining geometric and computer vision techniques. PLoS ONE. 2019;14(4):e0215521. https://doi.org/10.1371/journal.pone.0215521.
92. Vanegas F, Bratanov D, Powell K, Weiss J, Gonzalez F. A novel methodology for improving plant pest surveillance in vineyards and crops using UAV-based hyperspectral and spatial data. Sensors. 2018;18(1):260. https://doi.org/10.3390/s18010260.
93. Huang H, et al. A two-stage classification approach for the detection of spider mite- infested cotton using UAV multispectral imagery. Remote Sens Lett. 2018;9(10):933–41. https://doi.org/10.1080/2150704X.2018.1498600.
94. Joalland S, et al. Aerial and ground based sensing of tolerance to beet cyst nematode in sugar beet. Remote Sens. 2018;10(5):787. https://doi.org/10.3390/rs10050787.
95. Hunt ER, Rondon SI. Detection of potato beetle damage using remote sensing from small unmanned aircraft systems. J Appl Rem Sens. 2017;11(02):1. https://doi.org/10.1117/1.JRS.11.026013.
96. Severtson D, Callow N, Flower K, Neuhaus A, Olejnik M, Nansen C. Unmanned aerial vehicle canopy reflectance data detects potassium deficiency and green peach aphid susceptibility in canola. Precis Agric. 2016;17(6):659–77. https://doi.org/10.1007/s11119-016-9442-0.
97. Rejeb A, Abdollahi A, Rejeb K, Treiblmaier H. Drones in agriculture: a review and bibliometric analysis. Comput Electron Agric. 2022;198:107017. https://doi.org/10.1016/j.compag.2022.107017.
98. Liller J, Goel R, Aziz A, Hester J, Nguyen P. Development of a battery free, solar powered, and energy aware fixed wing unmanned aerial vehicle. Sci Rep. 2025;15(1):6141. https://doi.org/10.1038/s41598-025-90729-2.
99. Fendji JLEK, Bayaola IK, Thron C, Fendji MD, Förster A. Cost-effective placement of recharging stations in drone path planning for surveillance missions on large farms. Symmetry. 2020;12(10):1661. https://doi.org/10.3390/sym12101661.
100. Delavarpour N, Koparan C, Nowatzki J, Bajwa S, Sun X. A technical study on UAV characteristics for precision agriculture applications and associated practical challenges. Remote Sens. 2021;13(6):1204. https://doi.org/10.3390/rs13061204.
101. Safie S, Khairil R. Regulatory, technical, and safety considerations for UAV-based inspection in chemical process plants: a systematic review of current practice and future directions. Transp Res Interdiscip Perspect. 2025;30:101343. https://doi.org/10.1016/j.trip.2025.101343.
102. Adade R, Aibinu AM, Ekumah B, Asaana J. Unmanned aerial vehicle (UAV) applications in coastal zone management—a review. Environ Monit Assess. 2021;193(3):154. https://doi.org/10.1007/s10661-021-08949-8.
103. Hartley RJAL, Henderson IL, Jackson CL. BVLOS unmanned aircraft operations in forest environments. Drones. 2022;6(7):167. https://doi.org/10.3390/drones6070167.
104. Stöcker C, Bennett R, Nex F, Gerke M, Zevenbergen J. Review of the current state of UAV regulations. Remote Sens. 2017;9(5):459. https://doi.org/10.3390/rs9050459.
105. Arjune S, Kumar VS. Precision agriculture: influencing factors and challenges faced by farmers in delta districts of Tamil Nadu. In: 2022 OPJU international technology conference on emerging technologies for sustainable development (OTCON), Raigarh, Chhattisgarh, India: IEEE; 2023. pp. 1–6. https://doi.org/10.1109/OTCON56053.2023.10113906.
106. Parmaksiz O, Cinar G. Technology acceptance among farmers: examples of agricultural unmanned aerial vehicles. Agronomy. 2023;13(8):2077. https://doi.org/10.3390/agronomy13082077.
107. Bhandari M, et al. Unmanned aerial system-based high-throughput phenotyping for plant breeding. Plant Phenome J. 2023;6(1):e20058. https://doi.org/10.1002/ppj2.20058.
108. Sanz D, Valente J, Cerro JD, Colorado J, Barrientos A. Safe operation of mini UAVs: a review of regulation and best practices. Adv Robot. 2015;29(19):1221–33. https://doi.org/10.1080/01691864.2015.1051111.
109. Padhiary M, Saha D, Kumar R, Sethi LN, Kumar A. Enhancing precision agriculture: a comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. Smart Agric Technol. 2024;8:100483. https://doi.org/10.1016/j.atech.2024.100483.
110. Mowla MN, Mowla N, Shah AFMS, Rabie KM, Shongwe T. Internet of things and wireless sensor networks for smart agriculture applications: a survey. IEEE Access. 2023;11:145813–52. https://doi.org/10.1109/ACCESS.2023.3346299.
111. Rashid AB, Kausik AK, Khandoker A, Siddque SN. Integration of artificial intelligence and IoT with UAVs for precision agriculture. Hybrid Adv. 2025;10:100458. https://doi.org/10.1016/j.hybadv.2025.100458.
112. Ghazal S, Munir A, Qureshi WS. Computer vision in smart agriculture and precision farming: techniques and applications. Artif Intell Agric. 2024;13:64–83. https://doi.org/10.1016/j.aiia.2024.06.004.
113. Avşar E, Mowla MN. Wireless communication protocols in smart agriculture: a review on applications, challenges and future trends. Ad Hoc Netw. 2022;136:102982. https://doi.org/10.1016/j.adhoc.2022.102982.
114. Alahe MA, et al. Cyber security in smart agriculture: threat types, current status, and future trends. Comput Electron Agric. 2024;226:109401. https://doi.org/10.1016/j.compag.2024.109401.
115. Amarasingam N, Salgadoe ASA, Powell K, Gonzalez LF, Natarajan S. A review of UAV platforms, sensors, and applications for monitoring of sugarcane crops. Remote Sens Appl Soc Environ. 2022;26:100712. https://doi.org/10.1016/j.rsase.2022.100712.
116. Mgendi G. Unlocking the potential of precision agriculture for sustainable farming. Discov Agric. 2024;2(1):87. https://doi.org/10.1007/s44279-024-00078-3.
117. Narzari R, Choudhury BU, Singhal G, Choudhary KK. A critical review of how UAVs can transform precision agriculture in the realm of agroecology. Discov Soil. 2025;2(1):28. https://doi.org/10.1007/s44378-025-00055-2.
118. Nahiyoon SA, et al. Recent development trends in plant protection UAVs: a journey from conventional practices to cutting-edge technologies—a comprehensive review. Drones. 2024;8(9):457. https://doi.org/10.3390/drones8090457.