Advances and challenges in the applications of drone systems in precision agriculture: A review

Rehana Kaousar[1,2], Guobin Wang[1,2], Mujahid Hussain[1,3], Muhammet Fatih Aslan[4], Baoju Wang[1,2], Yu Yan[1,2], Nadia Rafique[1,2], Cancan Song[1,2], Xuejian Zhang[5], Yubin Lan[1,2*]

(1. *College of Agricultural Engineering and Food Science, Shandong University of Technology, Zibo 255000, Shandong, China*;
2. *Shandong University of Technology Sub-center of National Center for International Collaboration Research on Precision Agricultural Aviation Pesticide Spraying Technology, Zibo 255000, Shandong, China*;
3. *Department of Plant Science, Faculty of Agricultural and Food Sciences, University of Manitoba, 66 Dafoe Road, Winnipeg, MB, R3T 2N2, Canada*;
4. *Department of Artificial Intelligence and Machine Learning, Faculty of Computer and Information Sciences, Konya Technical University, Konya 42000, Turkey*;
5. *Economy and Information Technology, Ningxia Academy of Agriculture and Forestry Sciences, Yinchuan 750003, China*)

Abstract: Climate change, resource limitations, and increasing global food demand are accelerating the need for efficient and sustainable agricultural management practices. Unmanned aerial vehicles (UAVs) have emerged as a transformative technology in precision agriculture (PA) because of their capability to provide high-resolution, real-time, and site-specific crop monitoring. This review critically examines recent advancements (2016–2025) in UAV-assisted PA, focusing on UAV platforms, sensing technologies, data acquisition systems, information fusion methods, and artificial intelligence (AI)-driven analytical frameworks. Particular emphasis is placed on applications including crop monitoring, disease and pest detection, weed mapping, irrigation management, soil assessment, yield estimation, phenotyping, and precision spraying. The review highlights that integrating RGB, multispectral, hyperspectral, thermal, and LiDAR sensors with machine learning (ML) and deep learning (DL) algorithms substantially improves monitoring accuracy, operational efficiency, and agricultural decision-making compared with conventional practices. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), convolutional neural networks (CNNs), and YOLO-based models have demonstrated strong effectiveness in yield prediction, disease recognition, and weed discrimination. Despite these advancements, several challenges continue to limit large-scale implementation, including restricted flight endurance, payload limitations, environmental sensitivity, data-processing complexity, interoperability issues, and limited AI model transferability across different agricultural environments. Furthermore, model performance remains highly dependent on sensor configuration, dataset quality, and field-specific environmental conditions. Recent developments indicate rapid commercialization of UAV technologies together with emerging trends in edge AI, explainable AI (XAI), UAV–IoT integration, cloud-based analytics, and autonomous multi-UAV systems. Overall, this review identifies major technological advancements, key operational limitations, and future research directions required to support scalable, reliable, and climate-resilient UAV-assisted agricultural systems.

Keywords: precision agriculture, unmanned aerial vehicles, artificial intelligence, machine learning, deep learning, crop monitoring

DOI: 10.25165/j.ijabe.20261903.9288

Citation: Kaousar R, Wang G B, Hussain M, Aslan M F, Wang B J, Yan Y, et al. Advances and challenges in the applications of drone systems in precision agriculture: A review. Int J Agric & Biol Eng, 2026; 19(3): 1–19.

1 Introduction

Global agriculture is facing unprecedented pressure due to rapid population growth, climate change, land degradation, and increasing competition for water and energy resources[1,2]. According to the Agriculture in 2050 Project, the global population is expected to reach approximately 10 billion by 2050, requiring food production to increase by nearly 70% to meet future demand[3]. Simultaneously, climate variability is intensifying the frequency of droughts, heat stress, pest outbreaks, and soil degradation, placing additional pressure on conventional farming systems. These challenges highlight the urgent need for more efficient, resilient, and environmentally sustainable agricultural practices.

Traditional agricultural management often relies on uniform

Received date: 2024-08-10 **Accepted date:** 2026-05-09

Biographies: Rehana Kaousar, PhD Scholar, research interest: crop protection, Email: rehanakaousar916@gmail.com; **Guobin Wang**, Associate Professor, research interest: precision agriculture, Email: guobinwang@sdut.edu.cn; **Mujahid Hussain**, PhD Scholar, Postdoctoral, research interest: precision agriculture, Email: mujahidagr@gmail.com; **Muhammet Fatih Aslan**, Associate Professor, research interest: precision agriculture, Email: mfatihaslan@kmu.edu.tr; **Baoju Wang**, PhD Scholar, research interest: precision agriculture, Email: wbj@sdut.edu.cn; **Yu Yan**, PhD Scholar, research interest: precision agriculture, Email: 24603010025@stumail.sdut.edu.cn; **Nadia Rafique**, PhD Scholar, research interest: precision agriculture, Email: nadiarafique5555@gmail.com; **Cancan Song**, Associate Professor, research interest: precision agriculture, Email: songcc@sdut.edu.cn; **Xuejian Zhang**, Professor, research interest: precision agriculture, Email: xuejian-zhang@21cn.com.

***Corresponding author: Yubin Lan**, Professor, Dean, research interest: precision agriculture. College of Agricultural Engineering and Food Science, Shandong University of Technology, Zibo 255000, China. Tel: +86-533-2782718, Email: ylan@sdut.edu.cn.

field treatments and periodic visual inspections. However, such approaches often fail to capture the substantial spatial and temporal variability that exists within agricultural fields. These limitations have accelerated the development of PA, a data-driven management strategy that aims to optimize agricultural inputs and outputs through site-specific monitoring, analysis, and intervention[4]. According to the International Society for Precision Agriculture (ISPA), PA is a management approach that collects, processes, and analyzes temporal, spatial, and individual plant or animal data and integrates it with other relevant information to improve resource efficiency, productivity, profitability, quality, and sustainability in agricultural production[5].

The rapid advancement of information and communication technologies (ICT) has significantly contributed to the evolution of modern PA systems. Technologies such as remote sensing, Global Positioning Systems (GPS), Geographic Information Systems (GIS), Internet of Things (IoT), wireless sensor networks (WSNs), cloud computing, and AI now enable real-time monitoring, data-driven analysis, and precision decision-making in agricultural management[6,7]. These technologies facilitate efficient utilization of agricultural inputs while minimizing the environmental impacts associated with excessive application of fertilizers, pesticides, and irrigation water[8].

Among these technologies, UAVs, commonly referred to as drones, have emerged as transformative tools in modern precision agriculture due to their operational flexibility, rapid deployment capability, and ability to acquire ultra-high-resolution imagery in near real time. Compared with satellite and manned aircraft platforms, UAVs provide superior spatial and temporal resolution while minimizing operational complexity and cloud-related limitations. Modern agricultural UAVs can be equipped with RGB, multispectral, hyperspectral, thermal infrared, and LiDAR sensors, enabling detailed characterization of crop health, canopy structure, soil variability, water stress, disease incidence, weed infestation, and biomass dynamics[9].

Drone-based remote sensing has proven particularly effective for crop monitoring and early stress detection. Vegetation indices derived from multispectral imagery - such as the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), and Normalized Difference Red Edge (NDRE) - can detect changes in plant vigor, nutrient status, and water stress before visible symptoms appear, allowing timely management interventions[1]. Thermal sensors further enhance this capability by identifying canopy temperature anomalies associated with water stress, especially in high-value crops such as vineyards and orchards. In addition, LiDAR-equipped UAVs enable three-dimensional mapping of canopy structure and terrain, improving biomass estimation and supporting variable-rate application (VRA) strategies. Beyond monitoring, UAVs are increasingly used for interventional tasks, including precision spraying and targeted fertilization, thereby reducing chemical use and off-target environmental impacts[10,11].

The effectiveness of drone-based PA has been greatly improved by the integration of AI, ML, DL, and IoT technologies[12,13]. AI-driven analysis of UAV imagery enables automated detection of crop diseases, pest infestations, and nutrient deficiencies with reported classification accuracies exceeding 90% in several recent studies[14]. Coupled with IoT-enabled ground sensors and cloud-based analytics, UAVs now support near-real-time decision-making for irrigation scheduling, yield estimation, and site-specific crop management. This convergence of sensing, analytics, and automation is accelerating the transition toward data-driven and semi-autonomous farming systems[15,16].

Despite these substantial advances, several technical, operational, economic, and regulatory challenges continue to limit the large-scale adoption of UAV-based PA systems. Given the rapid pace of technological innovation and the expanding body of literature, a comprehensive and up-to-date synthesis is needed. This review provides a holistic overview of drone-based systems in PA, drawing primarily on studies published between 2016 and 2025 while also acknowledging foundational work from earlier years to capture long-term technological evolution. The review systematically examines drone platforms, sensor payloads, and analytical methodologies, links them to specific agricultural applications, and highlights key trade-offs in system design and deployment. Importantly, it also addresses persistent challenges, such as limited battery endurance, data processing complexity, regulatory barriers, and economic accessibility, which continue to constrain large-scale adoption. By integrating recent advances with unresolved limitations, this review aims to inform researchers, practitioners, and policymakers and to guide future research toward scalable, sustainable, and practical drone-based farming solutions (see Figure 1).

2 Literature search strategy and study selection

The analysis presented in this section is based on a curated dataset of 155 field-validated studies published between 2016 and 2025, retrieved from major scientific databases including Scopus, Web of Science, ScienceDirect, PubMed, and Google Scholar. The selected literature covers major UAV-assisted PA applications. The composition and characteristics of the reviewed dataset are illustrated in Figure 2. Figure 2a shows the distribution of studies across different application domains, where yield estimation, pest and disease detection, and phenotyping emerge as the most dominant research areas. In contrast, applications such as spraying and soil mapping are comparatively less explored, indicating potential research gaps. Figure 2b shows the studies carried out in each field numerically in a bar chart between 2016 and 2025. This trend highlights the rapid advancement of UAV technologies and the growing integration of ML and DL approaches in PA. Notably, approximately 75% of the studies were published after 2020, reflecting the accelerated adoption of AI-driven analytical frameworks. Across these application domains, methodological differences are evident. Machine learning techniques are commonly applied to structured datasets, whereas DL models dominate image-based analysis due to their superior capability in feature extraction and pattern recognition.

Figure 2c illustrates the geographical distribution of studies, with the majority originating from China, Europe, and the United States, demonstrating their leading role in UAV-based agricultural research. However, relatively limited contributions from regions such as Africa and parts of Asia indicate a geographical imbalance and highlight the need for broader global research representation. Figure 2d summarizes the diversity of crops investigated, including major field crops such as wheat, maize, and rice, along with various horticultural and perennial crops, demonstrating the wide applicability of UAV-based remote sensing across different agricultural systems. Despite this diversity, the dominance of staple crops suggests that region-specific and underrepresented cropping systems require further investigation.

Despite significant progress, several limitations remain. A major limitation across current UAV-based PA studies is the lack of

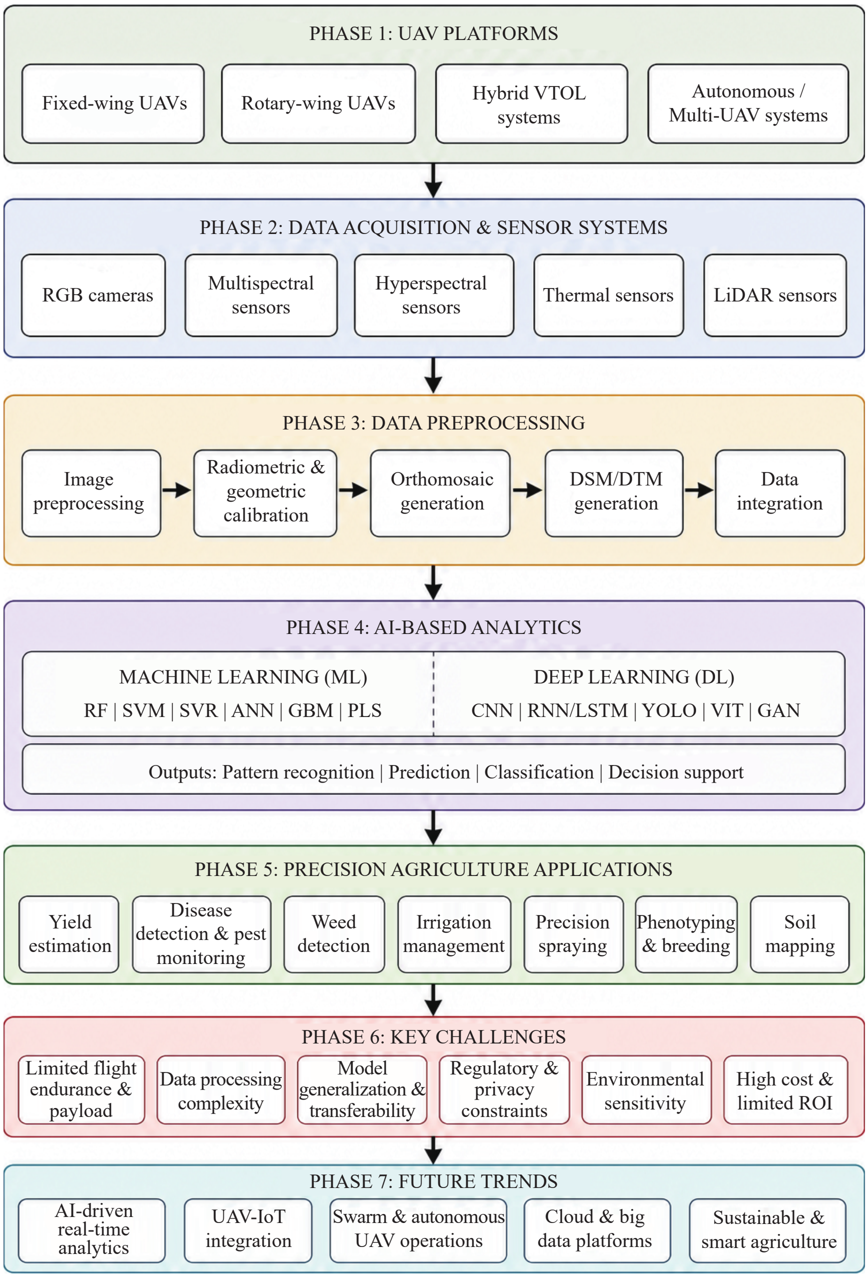

Figure 1 Workflow of UAV-based precision agriculture systems, including sensing technologies, AI-based analytics, agricultural applications, key challenges, and future trends

standardized protocols for sensor calibration, data acquisition, and model validation. Many studies are conducted under highly controlled conditions and rely on crop-specific datasets, limiting model transferability across environments and farming systems. Furthermore, insufficient integration between sensing outputs and practical farm management decisions restricts large-scale commercial adoption.

3 UAV platform types

Unmanned aerial vehicles (UAVs), commonly referred to as drones, are autonomous or remotely operated aerial platforms increasingly utilized in PA for high-resolution sensing, field monitoring, and site-specific crop management. Agricultural UAVs typically range from 2 to 20 kg depending on platform configuration, payload capacity, and operational objectives[17]. Recent advancements in lightweight materials, battery systems, flight-control technologies, and sensor integration have significantly improved UAV endurance, stability, and operational flexibility, accelerating their use in PA. Platform selection in PA is primarily influenced by agronomic requirements such as field scale, target resolution, crop type, and operational conditions. UAVs used in agricultural applications are generally classified into five categories based on aerodynamic configuration: fixed-wing, rotary-wing, hybrid vertical take-off and landing (VTOL), flapping-wing, and parafoil-wing systems (Figure 3 and Table 1). Among these categories, fixed-wing, rotary-wing, and hybrid VTOL platforms are the most commonly used in modern agricultural operations.

Fixed-wing UAVs resemble conventional airplanes and use aerodynamic lift to achieve longer flight endurance and wider field coverage. These platforms are particularly suitable for large-scale field mapping, vegetation monitoring, biomass estimation, and regional crop assessment[18]. However, fixed-wing UAVs generally require dedicated launch and landing areas and provide limited hovering capability. Rotary-wing UAVs, especially multirotor systems, are currently the most extensively used platforms in PA because of their vertical takeoff and landing capability, hovering

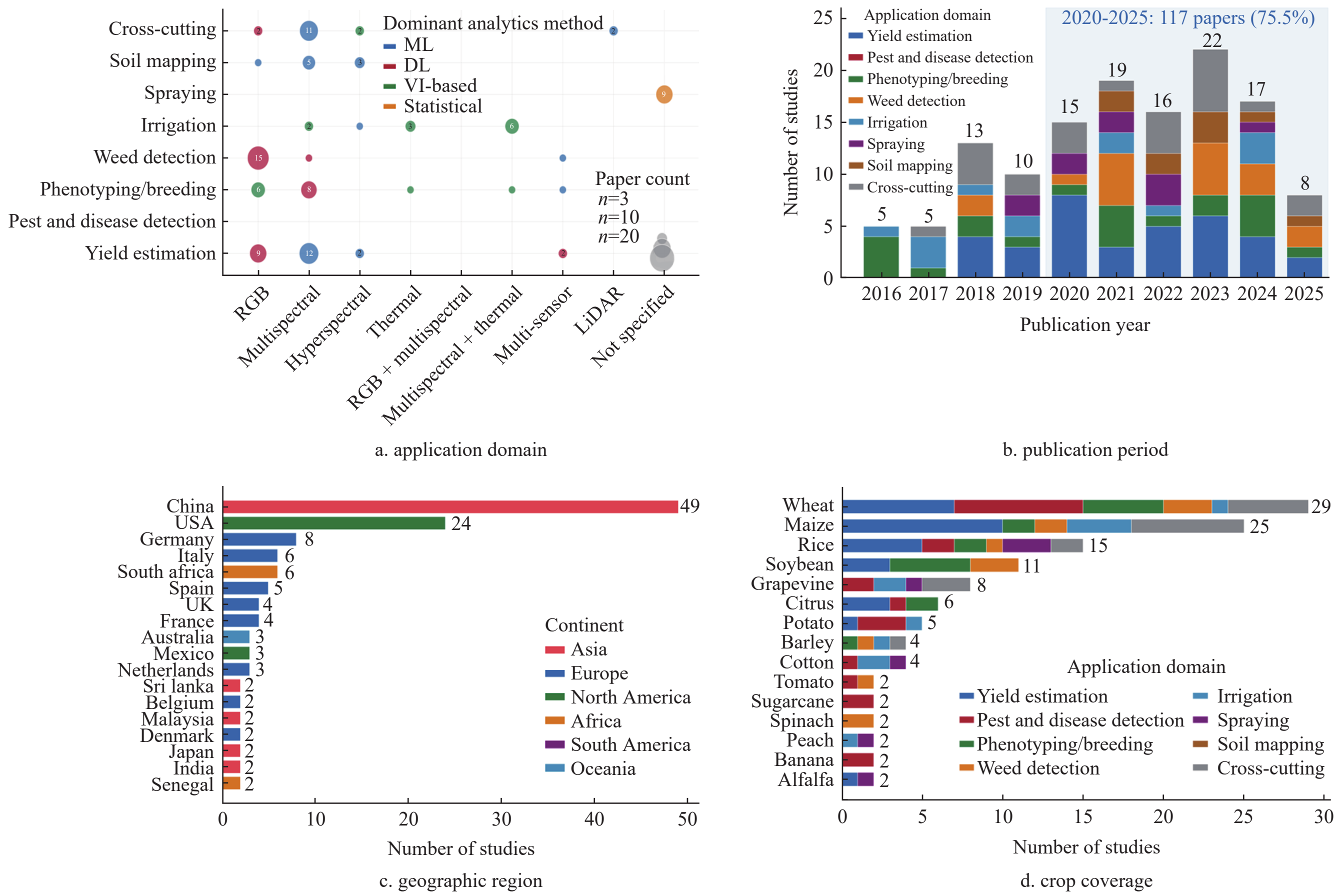

Figure 2 Composition of the final literature dataset by (a) application domain, (b) publication period, (c) geographic region, and (d) crop coverage

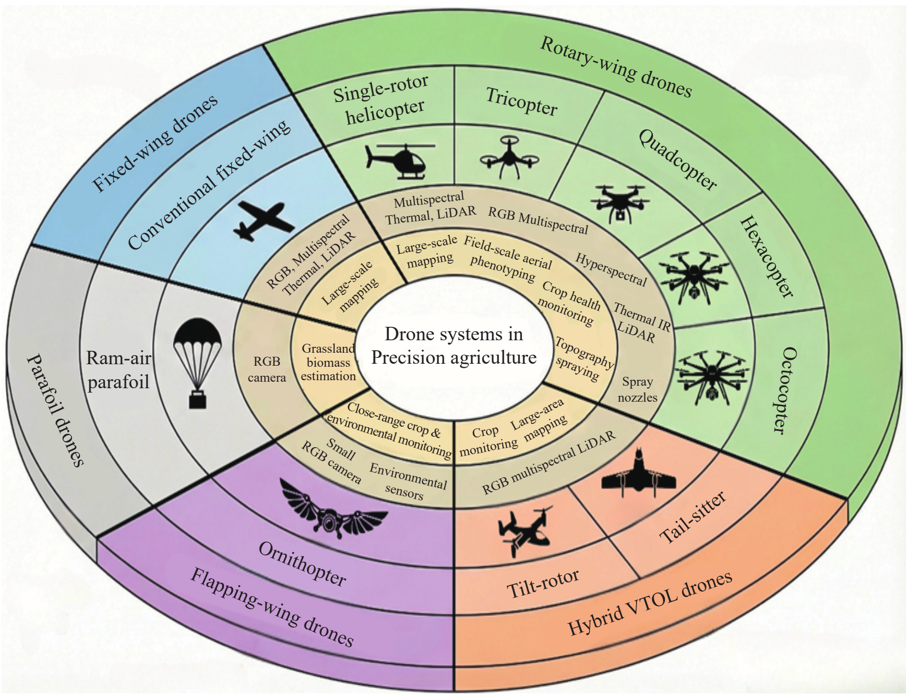

Figure 3 Major UAV platform configurations used in precision agriculture and their associated sensor payloads and agricultural applications

stability, maneuverability, and suitability for low-altitude imaging applications[19]. Rotary-wing UAVs may include single-rotor helicopters or multi-rotor configurations such as tricopters, quadcopters, hexacopters, and octocopters[20]. These platforms can acquire ultra-high-resolution imagery at low altitudes, enabling detailed crop monitoring, disease detection, canopy temperature assessment, phenotyping, and precision spraying. However, multirotor UAVs generally exhibit lower flight endurance and reduced area coverage compared with fixed-wing systems due to higher energy consumption during hovering operations.

Hybrid VTOL systems combine the vertical takeoff and landing capability of multirotor platforms with the flight efficiency of fixed-wing UAVs, providing improved operational flexibility and extended flight duration without requiring conventional runways[21,22]. In contrast, flapping-wing and parafoil-wing UAVs remain largely experimental in agricultural environments, with limited practical implementation in field-scale PA applications.

Table 1 UAV platforms and sensor systems commonly used in PA applications

UAV	Sensors	Reference
Fixed wing	Multispectral camera	[23]
Helicopter	Multispectral	[24]
Tricopter	Hyperspectral camera	[25]
Quadcopter	Digital camera	[26]
Hexacopter	GPS system	[27]
Octocopter	LiDAR	[28]
Flapping-wing	Thermal infrared sensors	[29]
Hybrid wing	RGB camera	[30]
Parafoil wing	RGB, Multispectral	[31]

Modern agricultural UAVs can be equipped with RGB, multispectral, hyperspectral, thermal infrared, and LiDAR sensors depending on the target application and operational requirements. These sensing systems support applications such as vegetation monitoring, disease detection, irrigation management, biomass estimation, and terrain analysis. The integration of UAV sensing technologies with GPS, GIS, artificial intelligence (AI), IoT, and cloud-based analytical systems has substantially improved the efficiency, automation, and decision-support capability of UAV-assisted PA. More detailed information about the types of UAVs used in PA applications can be found in the study by Radoglou-Grammatikis et al.[32]

4 UAV data acquisition and sensor systems

The selection of UAV sensors should be guided by the biological target and agronomic objective because each sensing modality captures different physiological and structural characteristics of crop canopies. Modern agricultural UAVs are designed to support a wide range of sensing payloads, including RGB, multispectral, hyperspectral, thermal infrared, LiDAR, and synthetic aperture radar (SAR) sensors, enabling high spatial and temporal resolution monitoring of agricultural systems.

Red-green-blue (RGB) cameras are widely used for vegetation and terrain mapping because of their high spatial resolution, low operational cost, and suitability for plant counting, canopy cover estimation, and morphological analysis[33]. Multispectral sensors capture reflectance in selected spectral bands, particularly red-edge and near-infrared wavelengths, enabling vegetation indices such as NDVI, GNDVI, NDRE, and SAVI for crop health, biomass, nutrient, and stress assessment[34]. Hyperspectral sensors acquire hundreds of narrow spectral bands, providing detailed biochemical information for detecting nutrient deficiencies, diseases, and water stress. Although highly accurate, their large data volume, calibration complexity, and computational demands limit large-scale deployment[35].

Thermal sensors measure canopy temperature using infrared radiation and are highly adaptable for irrigation management and crop water stress monitoring because canopy temperature variations are closely associated with stomatal conductance and transpiration rates[36]. UAV-based thermal and RGB imagery have also been successfully integrated with ML and DL approaches for wheat yield estimation and biomass assessment under water-stressed conditions. Additionally, LiDAR sensors emit near-infrared laser pulses and measure return times to reconstruct three-dimensional canopy structures. These systems are particularly valuable for biomass estimation, crop phenotyping, canopy height analysis, and terrain modeling[37].

Despite their high accuracy in complex canopies, widespread adoption is constrained by high operational and computational costs. In practice, no single sensor modality is sufficient to address the full range of precision agriculture objectives. Increasingly, multi-sensor integration - such as combining RGB, multispectral, thermal, and LiDAR data - is adopted to exploit complementary information and improve robustness of agronomic assessments. Recent studies demonstrate that sensor fusion, coupled with ML and DL algorithms, significantly improves the accuracy of yield prediction, disease detection, and water stress assessment compared to single-sensor approaches. However, multi-sensor systems also increase operational complexity, data volume, and computational demands, underscoring the need for optimized sensor selection aligned with platform capabilities and application-specific requirements (Figures 3 and 4; Table 2).

a. RGB camera b. Thermal camera c. Multispectral sensor

d. Hyperspectral camera e. LiDAR

Figure 4 Some sensors that UAV employ for PA

Table 2 Sensor modalities for UAV-based crop assessment: spectral characteristics, biophysical targets, and operational limitations[34]

Sensor	Spectral range/nm	Bands	Key Biophysical Target	Weight/g	Cost/USD	Limitations
RGB	400-700	3	Canopy structure, morphology, plant count, canopy cover	40-150	200-800	No red-edge or NIR; late visible stress
Multispectral	400-950	4–10	Chlorophyll status, LAI, early stress detection	100-300	3000-8000	Needs reflectance calibration; limited biochemical specificity
Hyperspectral	400-2500	100–600	Pigment biochemistry, leaf water content, pathogen fingerprints	200-1500	15 000-80 000	Heavy; high data volume; requires stable motion
Thermal IR	7500-4000	1	Canopy temperature, stomatal conductance, CWSI	130-400	5000-15 000	Sensitive to wind; limited flight window; soil interference
LiDAR	905 or 1550	1 (laser)	Canopy height, biomass, 3D architecture, lodging	500-2000	15 000-80 000	Expensive; heavy; no biochemical information

4.1 UAV data preprocessing and information fusion

UAV image pre-processing is a critical step for ensuring accurate spatial, spectral, and temporal analysis. UAV data pre-processing includes multispectral band distortion correction, orthorectification, mosaicking, and vegetation index (VI) generation. Large UAV datasets require substantial computational resources, storage capacity, and advanced analytical workflows. Ortho-photos are stitched from many partially overlapping aerial images, producing geometrically corrected (orthorectified) outputs[31]. Commercial data processing applications such as Agisoft PhotoScan, Adobe Photoshop, and Pix4DMapper (as listed in Table 3) commonly incorporate pre-processing functionalities to generate final data products such as digital surface models (DSM) and digital terrain models (DTM), as illustrated in Figure 5[38]. These software platforms also support radiometric calibration and surface reflectance generation for vegetation index analysis. The generated spectral reflectance maps play a significant role in calculating vegetation indices for monitoring crop growth and stress conditions[34].

Table 3 Various software used for crop monitoring

Software	Description	Reference
Pix4D	It can be used to calculate vegetation indices and create 3D models and orthomosaics.	[39]
Adobe Photoshop	Useful for fixing distortion and utilizing various image processing techniques	[40]
Agisoft PhotoScan	It provides mosaicking and straightening of TIFF images, including steps such as image loading, alignment, density point cloud, mesh, and texture generation.	[41]
ArcGis	Used for the image analysis and determination of NDVI	[42]
MATLAB	Used for image acquisition, processing, and computer vision and determination of vegetation indices	[43]
QGIS/ Python	It is commonly used for the spatial and temporal distribution of the NDVI index. Vegetation indices	[44]

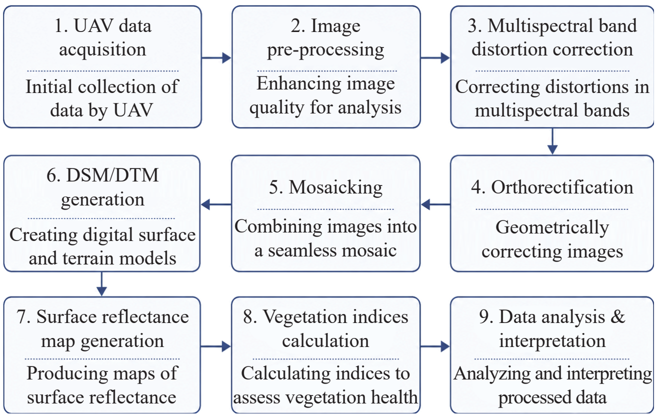

Figure 5 UAV data processing workflow

Data processing is particularly critical in UAV-based remote sensing because raw image datasets often contain large amounts of noise, illumination variability, geometric distortions, and environmental interference. Preprocessing techniques include image enhancement, segmentation, radiometric correction, geometric correction, and feature extraction to improve interpretation accuracy and decision-making performance. Additionally, photogrammetry, which provides information on three-dimensional crop characteristics, has become one of the most frequently used approaches for analyzing UAV imagery in PA. Recent advances in AI and computer vision have further enabled the automation of many processing stages, reducing manual interpretation requirements and improving analytical efficiency.

Information fusion challenges differ substantially between point-based and area-based approaches. Point-based fusion methods, including spectral signatures, vegetation index, color descriptors, and texture features, are computationally efficient and suitable for conventional ML workflows. However, these approaches are highly sensitive to illumination variability, sensor calibration inconsistencies, and background noise[45]. Variations in illumination conditions during UAV flights can introduce substantial spectral inconsistencies, particularly in vegetation indices derived from multispectral imagery[35]. In addition, point-based features often lack sufficient spatial context to fully capture canopy heterogeneity and complex plant interactions, limiting their robustness under variable field conditions.

In contrast, area-based fusion approaches using hyperspectral, multispectral, thermal, and LiDAR-derived imagery provide richer spatial, spectral, and structural information for crop assessment and stress detection. Nevertheless, these datasets introduce substantial computational challenges due to high dimensionality, large storage requirements, and increased processing complexity[46]. Hyperspectral datasets may generate 5-15 GB of data per survey, requiring extensive computational resources for processing and analysis. Accurate image alignment, radiometric correction, geometric correction, and multi-temporal registration also become critical for reliable integration of area-based datasets[47]. Furthermore, spectral redundancy within hyperspectral imagery may increase model complexity and overfitting risk if dimensionality reduction techniques are not properly applied. Push-broom hyperspectral sensors may additionally introduce geometric distortions during UAV movement under windy conditions, further complicating data fusion and interpretation[46]. Balancing computational efficiency with analytical accuracy, therefore, remains a major challenge in UAV-based multi-source data fusion systems.

4.2 Feature extraction methods for crop assessment

Feature extraction is a critical step in UAV-based data analysis, as it enables the identification and isolation of meaningful patterns from complex and high-dimensional datasets. In agricultural applications, feature extraction facilitates the transformation of raw sensor data into interpretable variables that support decision-making processes such as crop monitoring, disease detection, yield estimation, weed identification, and soil property assessment[48]. UAV platforms equipped with RGB, multispectral, hyperspectral, thermal, and LiDAR sensors generate diverse spatial, spectral, and structural information that requires application-specific feature extraction strategies. Traditional feature extraction approaches primarily rely on manually engineered (hand-crafted) features derived from domain knowledge. These include spectral vegetation indices such as NDVI, color features, texture descriptors including Gray-Level Co-occurrence Matrix (GLCM), and structural parameters derived from photogrammetry or LiDAR datasets[49,50].

Spectral features are widely used for crop vigor, biomass, nutrient, and stress assessment because they are computationally efficient and relatively easy to interpret. However, their performance may decrease under variable illumination conditions and heterogeneous soil backgrounds. Texture-based features provide improved discrimination capability for disease detection, weed mapping, and canopy characterization because they capture local spatial variability within crop canopies. Nevertheless, texture descriptors are highly sensitive to image resolution, noise, and environmental variability. Structural features derived from LiDAR and photogrammetric analysis are particularly suitable for crop height estimation, canopy architecture analysis, and phenotyping applications.

Despite their effectiveness, these methods require accurate georeferencing and computationally intensive processing workflows[51]. The suitability of feature extraction techniques therefore depends on the sensor type, biological target, and operational requirements of the UAV system. In practice, feature extraction serves as a fundamental stage for subsequent ML and DL analyses because the quality and relevance of extracted features strongly influence model accuracy and robustness under real-field agricultural conditions[52].

4.3 Machine learning (ML) algorithms

Machine learning algorithms are widely used in UAV-assisted precision agriculture for classification, regression, clustering, and predictive analytics using multisource agricultural datasets[53,54]. Unsupervised and supervised learning techniques are commonly utilized, including clustering, classification, and regression algorithms. The categorization of ML methods is shown in Figure 6.

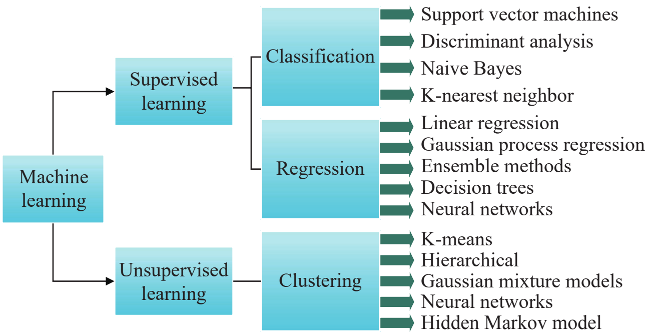

Figure 6 Overview of machine learning algorithms

The suitability of ML algorithms varies considerably depending on data structure, computational resources, and application objectives. Traditional ML algorithms such as Linear Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Support Vector Regression (SVR), and Artificial Neural Networks (ANN) are computationally efficient and generally perform well with structured datasets and limited training samples[53,54]. These approaches are particularly suitable for vegetation index analysis, biomass estimation, crop classification, and regression-based yield prediction tasks. However, conventional ML methods often exhibit limited capability in capturing complex nonlinear relationships and spatial variability within high-resolution UAV imagery, reducing their robustness under heterogeneous field conditions[55].

Among these methods, RF is widely preferred because of its robustness against overfitting, ability to handle nonlinear relationships, and strong performance with multispectral and vegetation index datasets[56]. RF algorithms are especially suitable for crop yield estimation, soil property mapping, and irrigation monitoring applications. However, RF models often struggle to extract complex spatial patterns from high-resolution UAV imagery compared with deep learning approaches[55]. Support Vector Machine and Support Vector Regression algorithms are highly effective for small and medium-sized agricultural datasets and have demonstrated strong classification performance for disease detection and crop discrimination tasks[57]. Nevertheless, SVM-based methods become computationally expensive when processing large-scale UAV image datasets with high dimensionality.

Linear Regression models are simple, interpretable, and computationally inexpensive, making them suitable for rapid vegetation index analysis and preliminary yield prediction studies. However, LR approaches have limited capability for modeling complex nonlinear agricultural relationships. ANN models provide improved nonlinear modeling performance for crop growth and water stress prediction applications, although their performance remains sensitive to training data quality and hyperparameter selection[58]. Overall, ML algorithms are advantageous in applications involving moderate computational resources, structured numerical features, and limited annotated datasets. However, their limited automatic feature extraction capability and weaker spatial learning performance reduce effectiveness for highly complex image-based agricultural applications compared with DL methods[53]. Recent UAV-based ML applications in PA are summarized in Table 4.

Table 4 UAV & PA applications using ML and DL algorithms

Study	PA application	Crop	UAV	Equipments	Classification/Detection	Software	No. of images	Acc/ %	Loss/ %	No. of classes
Su et al.[61]	Wheat Yellow Rust identification	Wheat	DJI Matrice 100 (M100)	Multispectral orthomosaic, RedEdge camera, RGB-NIR	DL, U-Net, Convolutional Neural Networks CNN, RF	-	100	84.1	5	1
Maimaitijiang et al.[62]	Grain yield prediction	Soybean	DJI S1000, Octocopter	Multispectral, RGB and thermal images	DNN, RFR PLSR, SVR, SVM, DSM, DEM	Pix4Dmapper	-	72	15.9	2
Che'Ya et al.[59]	Weed detection	Sugarbeet	Autonomous Robotti	Multispectral GPS system IMU	YOLOv3 for object detection	-	2260	57	5	2
Darwin et al.[63]	Pest infestation analysis	Apple, grapes	DJI Matrice 600	Multispectral, Hyperspectral,	CNN, ResNet, SVM	-	-	92.5	-	-
Zheng et al.[60]	Flower and fruit stage detection	Strawberry	DJI Inspire 2	RGB Multispectral, LiDAR	(Faster R-CNN)	-	-	84.1	-	4
Alves et al.[64] Wang et al.[65]	Pest identification	Cotton	DJI Phantom 4, multispectral	RGB images	ResNet34, CNN	-		98.1	-	1
Garza et al.[66]	HLB disease detection	Citrus	DJI Phantom 4	Multispectral images	SAM	ITT VIS	-	87	-	1
Schirrmann et al.[67]	Nitrogen and biophysical assessment	Wheat	Hexacopter P-Y6	RGB	Linear regression, surface models (M1-3)	Agisoft Lens software	-	10-11	13,37	1
Apolo-Apolo et al.[68]	Fruit detection and yield estimation	Citrus	Quadcopter DJI Phantom3P	RGB, digital camera	ANN, Machine vision algorithm	-	96	75.3	24.7	3
Apolo-Apolo et al.[69]	Yield prediction	Apple, mango	DJIPhantom 4 Pro	RGB and YCbCr	R-CNN	Agisoft PhotoScan Professional 1.2.3	593	51	2.4	1
Liu et al.[70]	Recognition and monitoring	Fuji apple	DJI M600 Pro	RGB	Support vector regression (SVR), classification and regression tree (CART)	SPSS, Pix4D Mapper, ENVI	60	92.2	1.5	1
Chandel et al.[71]	Powdery mildew detection	Strawberry	DJI Phantom 4 Pro	RGB, Multispectral	ANNs and SVMs	MATLAB R2019a, Pix4D	254	94.34, 88.98	-	1

4.4 Deep learning (DL) approaches

Deep learning, a subset of ML, has gained considerable attention in PA because of its automatic feature extraction and pattern recognition capabilities. Unlike conventional ML methods, DL architectures can directly learn hierarchical spatial and spectral features from UAV imagery without requiring manual feature engineering[72,73]. CNNs are among the most widely used DL architectures for UAV-based agricultural applications including crop classification, disease detection, weed mapping, and canopy segmentation because of their strong spatial feature extraction capability[74,75]. CNN-based approaches generally outperform traditional ML methods when large annotated image datasets are available. However, CNN models require extensive computational resources, large labeled datasets, and long training times, which may limit their deployment in resource-constrained agricultural systems[76,77].

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are more adaptable for temporal and sequential agricultural datasets because they can capture crop growth dynamics across multiple time-series observations. These methods are particularly suitable for crop growth monitoring, seasonal yield forecasting, and phenological analysis. Nevertheless, RNN-based architectures are computationally complex and may suffer from gradient instability during long-sequence training[72]. Object detection architectures such as YOLO and Faster R-CNN are highly suitable for real-time UAV applications including weed detection, pest monitoring, and fruit counting because of their fast inference capability and efficient object localization performance[59,60]. YOLO-based models are advantageous for field-scale operational deployment due to their high processing speed. However, detection accuracy may decrease for very small or partially occluded targets under dense canopy conditions. Generative Adversarial Networks (GANs) are increasingly used for synthetic image generation and data augmentation when annotated agricultural datasets are limited, thereby improving model generalization and reducing overfitting[74]. However, GAN training procedures are often unstable and computationally demanding.

Recent hybrid architectures combining CNN and Vision Transformer (ViT) models have demonstrated improved feature representation and classification robustness in UAV-based agricultural monitoring systems, particularly under complex illumination and canopy conditions[78]. However, hybrid architectures require very large datasets and powerful hardware acceleration systems for efficient training and deployment. Despite their advantages, DL approaches still face important limitations related to transferability, interpretability, and generalization across different agricultural environments. Models trained under specific crop, environmental, or sensor conditions frequently exhibit reduced performance when applied to different agricultural systems due to variations in illumination, canopy architecture, soil background, and crop growth stages[79].

Furthermore, overfitting, limited interpretability, and dataset bias continue to restrict the scalability of AI-driven agricultural systems under real-world field conditions[80]. Consequently, transfer learning, explainable AI (XAI), hybrid ML-DL frameworks, and edge-computing-based AI systems are increasingly being explored to improve model generalization, robustness, and real-time deployment in UAV-assisted PA. Information on recent similar studies (after 2020) and the parameters comparing these studies are presented in detail in Table 4.

5 Applications of UAV in PA

Remote sensing (RS) plays a very important role in modern agriculture. Growers remotely monitor crops and soil health using a variety of sensors and technologies. In this way, crop and soil health status is visualized and evaluated in a low-cost and efficient manner at various stages of production. Applications for remote sensing with UAVs generally aim to detect problems that may occur in agriculture at an early stage. Recent advancements in UAV-based PA are largely driven by the integration of high-resolution sensing technologies and AI. The rapid increase in studies after 2020 reflects a transition from conventional monitoring approaches toward data-driven and predictive agricultural management systems.

While these application domains share common UAV-based sensing principles, they differ substantially in their biological targets, sensing requirements, spatial and temporal scales, and analytical complexity. Yield estimation primarily reflects biomass accumulation and canopy photosynthetic activity and therefore relies on multi-temporal canopy observations and predictive modeling. In contrast, disease and pest detection focus on identifying subtle physiological and morphological disturbances at early growth stages, requiring high spatial resolution and spectral sensitivity. Weed detection depends on ultra-high-resolution imagery and accurate plant-level discrimination, whereas irrigation management primarily utilizes thermal and hyperspectral sensing to assess crop water stress. Similarly, spraying applications require real-time positioning, droplet control, and environmental adaptability to ensure efficient chemical delivery. These differences demonstrate that UAV-based PA applications are not interchangeable and require task-specific sensor configurations, flight strategies, and analytical frameworks. Although remote sensing includes many subheadings, recent studies (2016–2025) show a wide range of UAV applications in PA. These applications can be categorized into the following domains: (a) Crop yield estimation, (b) Pest and disease detection, (c) Phenotyping and breeding, (d) Weed detection, (e) Irrigation and water stress monitoring, (f) Spraying, (g) Soil mapping, and (h) Cross-domain integration.

5.1 Crop yield estimation

Canopy spectral reflectance is widely used for crop yield estimation because grain filling largely depends on photosynthetic assimilate supply and canopy chlorophyll content[81]. However, spectral indices mainly represent source capacity and may not fully capture sink limitations caused by post-anthesis biotic or abiotic stresses. UAV-based yield prediction accuracy is strongly influenced by crop growth stage and data acquisition timing, with multi-temporal observations generally outperforming single-date surveys[82,83]. Maimaitijiang et al.[62] demonstrated that multisensor data fusion substantially improved prediction performance. For example, deep neural network (DNN) fusion of RGB, multispectral, and thermal imagery improved soybean yield prediction from R^2 = 0.52 to 0.72, while UAV-derived structural features achieved R^2 > 0.77 for mango yield estimation without direct fruit detection[84]. Apolo-Apolo et al.[68] estimated citrus yield per tree using LSTM deep learning applied to UAV RGB imagery in Spanish orchards, achieving substantially lower error than expert technicians.

Despite these promising results, model transferability remains a major limitation in UAV-assisted yield prediction. Killeen et al.[85] reported substantial reductions in prediction accuracy during spatial cross-validation, indicating strong dependence on localized environmental conditions and training datasets. Domain adaptation approaches provide partial solutions: Priyatikanto et al.[86] used DANN for cross-domain maize yield prediction in the US Corn Belt. Khaki et al.[87] achieved MAE below 9% for both corn and soybean using a single YieldNet architecture. Nevertheless, multi-site validation and shared training datasets remain limited, particularly for heterogeneous smallholder farming systems. Consequently, most UAV-based yield prediction models still lack the robustness and scalability required for routine commercial deployment. Representative UAV-based yield estimation studies across different crops and geographic regions are summarized in Table 5.

5.2 Disease detection and pest monitoring

UAV-based disease detection exploits pathogen-induced changes in leaf optical properties before visible symptoms appear. Fungal infections reduce chlorophyll and red-edge reflectance, bacterial infections alter near-infrared signals through mesophyll disruption, while viral infections modify pigment ratios, producing diffuse spectral responses[89]. These spectral and spatial signatures are effectively captured using UAV sensors and DL models, which outperform traditional vegetation indices. Sensor selection depends on the objective, with RGB used for severity mapping, multispectral for early detection, and hyperspectral for pathogen discrimination[90]. Detection accuracy depends on pathogen class, sensor, and growth stage, with hyperspectral studies achieving 85% to 98% overall accuracy (OA) for well-characterized fungal pathogens. Shi et al.[90] achieved 98.1% OA for potato late blight using CropdocNet, a DL architecture with capsule layers, applied to UAV hyperspectral imagery. Although transfer learning reduces annotation requirements, robust model training still requires large labeled datasets[91].

Crop pest monitoring using UAVs operates through two complementary approaches: indirect detection of herbivory-induced canopy changes via spectral sensors, and direct visual detection of pest damage symptoms using close-range RGB imaging[92]. Arthropod feeding alters leaf reflectance through chlorophyll loss and membrane disruption, producing spectral signatures detectable at canopy level before visual damage is apparent. Yu et al.[93] developed CPD-YOLO, an improved YOLOv8 model with a bidirectional feature pyramid network and dynamic detection heads, for simultaneous detection of cotton aphids, double-spotted leaf beetles, and brown spot disease from both UAV and smartphone RGB images, achieving mean average precision (mAP) = 90.4% with F1 = 88.9%.

Yu et al.[94] utilized time-series hyperspectral data acquired from UAV platforms to detect pine wilt disease (PWD) at early stages, demonstrating that temporal spectral variations can effectively identify infected trees prior to the appearance of visible symptoms. Narmilan et al.[95] used multispectral UAV imagery with XGBoost classification and achieved 94% accuracy for white leaf disease in sugarcane, a phytoplasma condition transmitted by leafhopper vectors. Such low-altitude imaging improves the detection of fine-scale feeding damage and increases sensitivity to early infestation symptoms compared with conventional canopy-level monitoring. Table 6 presents representative disease and pest detection results.

Table 5 Representative UAV-based yield estimation results. MS = multispectral; TIR = thermal; CV = cross-validation; SE = standard error. Growth stages use the Zadoks scale (Z) for cereals, BBCH for fruit crops, and Fehr scale (R/V) for soybean and maize

Crop	Stage	Sensor	Model	R^2/RMSE	Validation	Geography	Reference
Soybean	R5 (pod fill)	MS	RF, XGBoost	R^2=0.86	Hold-out	USA	[55]
Maize	VT–R3 (tassel–milk)	MS	RF multi-temporal	R^2=0.93	CV	China	[82]
Rice	Z55 (heading)	RGB+MS	RF fusion	R^2=0.85	Cross-year	China	[83]
Soybean	R3–R5	RGB+MS+TIR	DNN fusion	R^2=0.72	CV	USA	[62]
Mango	Fruit set (BBCH 69)	RGB	Tree structure+RF	R^2>0.77	Hold-out	Senegal	[84]
Citrus	Maturity (BBCH 87)	RGB	LSTM counting	SE=4.5%	Hold-out	Spain	[68]
Maize	R1–R3 (silk–milk)	Hyper+RGB	RF, XGBoost	R^2=0.81	CV	China	[88]

Table 6 Representative UAV-based disease and pest detection results. OA = overall accuracy; mAP = mean average precision; TL = transfer learning

Disease/Pest	Crop	Sensor	Architecture	Detection	Accuracy	Geography	Reference
Late blight	Potato	Hyperspectral	CropdocNet	Pre-symptomatic	98.1% OA	UK	[90]
Yellow rust	Wheat	Hyperspectral	DCNN	Mid-infection	85% OA	UK	[96]
Stem rust	Wheat	Hyperspectral	RFC	Symptomatic	85% OA	USA	[97]
7 phytopathogens	Wheat	Hyperspectral	RF	Symptomatic	94% OA	Kazakhstan	[98]
4 diseases	Wheat	MS	VGG16-SVM	Symptomatic	97% OA	Pakistan	[99]
White leaf disease	Sugarcane	RGB	YOLOv5	Symptomatic	93% mAP	Sri Lanka	[95]
BBTD/BXW	Banana	RGB+MS	RetinaNet	Symptomatic	99.4%	DR Congo	[100]
Bacterial blight	Rice	MS+TIR	LSTM TL	Symptomatic	R^2=0.82	China	[101]
HLB	Citrus	Hyperspectral	SAE-NN	Pre-symptomatic	99.7%	China	[102]
Phylloxera	Grapevine	Hyper+TIR	Statistical	Pre-symptomatic	Significant	Australia	[103]
Aphid+beetle+spot	Cotton	RGB (UAV+phone)	CPD-YOLO	Symptomatic	90.4% mAP	China	[93]

5.3 Soil property mapping

UAV reflectance sensors detect energy from only the topmost 0.1 to 1.0 mm of the soil surface, while plant-available nutrients reside at 100 to 1500 mm depth. Correlating surface reflectance with subsurface properties requires a stable relationship between surface and profile chemistry, an assumption violated by tillage, rain splash, and seasonal wetting. Under bare-soil conditions, SOM prediction achieves R^2 = 0.91 and RMSE = 0.13%[104]. Heil et al.[105] also showed the model transferability between neighboring fields. UAV-satellite fusion improves subsurface estimation: Zhu et al.[106] combined UAV texture with Sentinel-2B spectral data and improved prediction of salinity, nitrogen, and organic matter across

400 hectares. Table 7 presents representative soil mapping results.

Despite measurement advances, no published study has demonstrated that variable-rate management decisions based on UAV soil maps improve yield or reduce input costs relative to conventional grid sampling. Soil moisture at the time of flight is a confounding variable most studies do not measure. Tropical soil validation is absent. A replicated multi-site trial comparing agronomic outcomes under UAV-map-based versus grid-sampling-based management is the most needed research investment.

5.4 Weed detection and herbicide management

Weed-crop spectral discrimination is particularly challenging during early growth stages because weeds and crops often exhibit similar leaf area index (LAI) and chlorophyll characteristics[113]. UAV-assisted site-specific weed management has demonstrated substantial potential for reducing herbicide application by restricting spraying to weed-infested zones, resulting in chemical savings of 15%-41%[114,115].

YOLO architectures dominate UAV weed mapping. Mesías-Ruiz et al.[116] applied a YOLOv8m model to UAV RGB imagery of maize and tomato fields in Spain and achieved mAP = 0.93 for nine weed species, with over 70% of weed-infested zones correctly identified. Gallo et al.[117] used YOLOv7 for weed detection in chicory plantations, outperforming earlier YOLO variants on the same dataset. Vision Transformers (ViTs) have also shown improved classification performance under limited training datasets. Reedha et al.[118] showed that a vision transformer (ViT) exceeded EfficientNet and ResNet for crop-weed classification from UAV RGB imagery of beet and spinach fields. In addition, Anderegg et al.[119] conducted season-long weed monitoring using object-based image analysis (OBIA) across nine wheat sites, confirming that high GSD is critical at early growth stages. Table 8 presents representative weed detection results.

Table 7 Representative UAV-based soil property mapping results

Property	Sensor	Model	R^2/RMSE	Geography	Reference
SOM	Multispectral	RF	RMSE=0.13%	Germany	[105]
SOM	Multispectral	RF	R^2=0.91	China	[104]
SOC	Multispectral	RF	R^2=0.92	Spain	[107]
10 soil attributes	MS+Sentinel-2	RF	Improved vs single	China	[106]
Sand/silt/clay	Hyperspectral	PLSR, RF	Effective mapping	China	[108]
VWC, EC	MS+geophysics	RF	Significant improvement	USA	[109]
SOM	Hyperspectral	RF	R^2=0.69	Netherlands	[110]
SOC	RGB+SPIs+TAs	EGB	R^2val=0.86	Czech Republic	[111]
SOM, STN	Hyperspectral	PSO-ELM	R^2=0.73	China	[112]

Note: SOM = soil organic matter; SOC = soil organic carbon; VWC = volumetric water content; EC = electrical conductivity.

Table 8 Representative UAV-based weed detection results. mAP = mean average precision; OA = overall accuracy; OBIA = object-based image analysis; ViT = vision transformer; Herb. = herbicide

Weed Target	Crop	Sensor	Architecture	Accuracy	Herb. Reduction	Reference
9 species	Maize/Tomato	RGB	YOLOv8m	mAP=0.93	>70% weed-free	[116]
Broadleaf	Chicory	RGB	YOLOv7	mAP@0.5=57%	—	[117]
Multi-species	Wheat	RGB	OBIA	Season-long	—	[119]
Broadleaf	Rice	MS	DFNN	—	41% savings	[115]
Multi-species	Arable	RGB	RF-OBIA	High OA	Up to 50%	[114]
Crops vs weeds	Beet/Spinach	RGB	ViT	Outperformed CNN	—	[118]
Multi-species	Multiple	RGB	YOLOv4	93.4% mAP	—	[120]

Herbicide resistance monitoring remains an underexplored area because of biological and spectral complexities. Resistant weed biotypes may differ spectrally because metabolic resistance mechanisms alter chloroplast composition. No operational system for landscape-scale resistance monitoring exists. Foundation models pre-trained on diverse global weed databases could reduce per-species annotation requirements to fewer than 100 examples.

5.5 Variable-rate spraying and drift control

Rotor-induced downwash creates a directed airstream that drives spray droplets into lower canopy layers[121]. Wind is the dominant drift determinant. Wang et al.[122] measured drift at 12 m downwind at an order of magnitude lower than within the swath. Increasing droplet volume median diameter (VMD) from 95 to 185 μm reduced cumulative drift from 74% to 23% in rice field trials. Droplets below 160 μm require buffer zones of at least 10 m[123].

Variable-rate application (VRA) integrates sensing and spraying in a two-stage workflow: a prior sensing flight generates a pest or disease prescription map, and the spray platform executes it. Pesticide savings of 15%-41% are documented across rice[124], cotton, and vineyard[125]. Biglia et al.[126] achieved 309% higher canopy deposition using band spray mode in vineyard compared with broadcast application, while reducing ground losses by 70%. UAV spraying has its strongest case in terrain inaccessible to ground machinery. Life cycle assessment (LCA) studies are also emerging. Seo et al.[127] showed lower environmental impact for UAV spraying compared with boom sprayers in Japanese rice production. Safaeinejad et al.[128] reported that UAV spraying in Iranian wheat consumed 2.43 times less energy, with a global warming potential (GWP) of 14.5 vs. 41.3 kg CO_2/hm^2 for conventional methods (Table 9).

5.6 Water stress and irrigation scheduling

When soil water potential falls below a crop-specific threshold, the stomata close and reduce evaporative cooling, which leads to an increase in canopy temperature[36,131]. The crop water stress index (CWSI) normalizes this temperature differential by scaling the measured canopy temperature between a lower limit representing a fully transpiring, non-stressed canopy and an upper limit representing a non-transpiring canopy with fully closed stomata, thereby removing confounding effects of air temperature and vapor pressure deficit. Park et al.[36] validated UAV-derived CWSI against stem water potential in a nectarine orchard across four irrigation regimes, achieving R^2 = 0.82 with stomatal conductance. Midday flights (11:00 to 14:00) maximize the signal; however, early morning flights underestimate stress.

CWSI validation spans R^2 = 0.55 to 0.90 across crop systems, reflecting biological differences in stomatal regulation. Wang et al.[132] combined thermal and red-edge vegetation indices for winter wheat at six key growth stages and achieved R^2 = 0.88 for normalized stomatal conductance at the flowering stage using gradient boosting decision tree (GBDT). Brewer et al.[133] applied random forest to thermal and optical UAV imagery and predicted maize foliar temperature and stomatal conductance across phenological stages in South African smallholder farms, demonstrating transferability to resource-constrained systems. Kapari et al.[134] confirmed R^2 = 0.85 for CWSI prediction in maize in the same region, with NDRE and thermal infrared as the most important input variables. Thermal data also detects genotypic water use efficiency differences for breeding[135,136]. Variable-rate irrigation saves 15% to 30% vs. calendar-based schedules. Table 10 presents representative results.

Table 9 Representative UAV spray application studies. VMD = volume median diameter; VRA = variable-rate application; KMS = knapsack sprayer; CFD = computational fluid dynamics; LCA = life cycle assessment; GWP = global warming potential

Parameter	Crop	Platform	Key Finding	Reference
Droplet size	Rice	Quadcopter	VMD 95→185 μm reduced drift 74%→23%	[123]
Downwash vortex	Rice	Hexacopter	Clear vortex state: 1.5x deposition vs small-vortex	[121]
Drift distance	General	Quadcopter	Drift at 12 m downwind: order of magnitude lower	[122]
Band spray mode	Grapevine	Multirotor	309% higher canopy deposition; 70% less ground loss	[126]
Flight velocity	Peach	Multirotor	2 m/s optimal for peach deposition	[129]
UAV vs ground	Cotton	Multirotor	UAV more efficient than ground for defoliation	[125]
UAV vs KMS	Rice	Multirotor	30 L/ha UAV = 500 L/ha KMS weed control	[124]
CFD prediction	General	Multiple	SVR/BP deposition error <10%	[130]

Table 10 Representative UAV-based water stress and irrigation results. gs = stomatal conductance; SWP = stem water potential; LWP = leaf water potential; NGS = normalized stomatal conductance; GBDT = gradient boosting decision tree

Crop	Sensor	Stress Index	Model	R^2 vs gs/SWP	Geography	Reference
Nectarine	Thermal	CWSI	Empirical	R^2=0.82 (gs)	Australia	[36]
Wheat	Thermal+MS	NGS	GBDT	R^2=0.88	China	[132]
Maize	Thermal+MS	CWSI	RF	R^2=0.85	South Africa	[134]
Maize	Thermal+MS	Foliar temp	RF	Predicted gs	South Africa	[133]
Cotton	Thermal	CWSIsi	Empirical	R^2=0.66 (gs)	China	[131]
Cotton	Thermal	CWSI	Empirical	R^2=0.65 (LWP)	USA	[137]
Grapevine	Thermal+MS	CWSI	Empirical	R^2=-0.80 (Pn)	Italy	[138]
Maize	MS	EWT, FMC	RFR	rRMSE=3.1%	South Africa	[136]

Three constraints reduce reliability: midday-only flight windows, wind above 3 m/s introducing 1°C to 2°C CWSI error, and no internationally agreed CWSI reference protocol. Developing crop-specific thresholds under standardized methods would eliminate per-field calibration.

5.7 High-throughput phenotyping (HTP) for breeding

Plant breeding programs evaluate thousands of genotypes annually[139]. UAV-based high-throughput phenotyping offers non-destructive, time-series characterization of every plot simultaneously. The traits it measures are secondary traits correlated with yield through biological pathways that differ by crop and stress regime. Their precise and effective use requires understanding which trait is genetically linked to the breeding target and at which growth stage[140,141].

UAV-derived static and dynamic phenotypes improve genomic selection (GS) accuracy over manually collected traits. Kaushal et al.[142] showed that multi-trait GS incorporating UAV spectral indices improved wheat yield prediction from r = 0.23 to r = 0.40. Zhou et al.[143] demonstrated that LASSO selection matched 71% to 76% of breeder selections with 4 to 5% higher yield. Volpato et al.[144] applied deep CNNs to UAV RGB imagery of a rice diversity panel under drought stress in China. The practical value of UAV-based phenotyping lies in its capacity to reduce labor by over 90% while maintaining measurement quality comparable to ground methods. Alves et al.[145] demonstrated significant genotype-by-flight date interactions in Brazilian soybean, showing that the timing of UAV acquisition affects heritability estimates and must be standardized across breeding programs. Table 11 presents representative phenotyping results.

Standardized flight protocols, trait extraction pipelines, and multi-environment HTP datasets are the three research priorities. Minor and tropical crops remain underrepresented apart from sorghum, faba bean, and poplar.

5.8 Cross-domain integration

The seven application domains share a common information architecture that becomes more powerful when combined. Schut et al.[150] demonstrated this by integrating UAV-derived light interception with soil and fertilizer data in Mali smallholder fields, explaining 78% of yield variation and 74% of fertilizer response. Zhang et al.[151] achieved R^2 = 0.926 for SPAD by integrating satellite, UAV, and ground sensor data. Popescu et al.[152] showed that UAV-WSN-IoT collaboration improved data collection efficiency through consensus algorithms. Xu et al.[153] improved weed mapping OA by 5% by fusing spectral, textural, structural, and thermal UAV measurements. Table 12 presents evidence-based examples of multi-domain integration.

The interoperability barrier is institutional more than technical. Yield maps, soil maps, spray records, and disease observations use proprietary formats. ISOBUS enables machinery-prescription integration, but cross-domain georeferenced fusion is not standardized. Research programs designed for multi-domain data collection within the same field and season are the most valuable investment[154]. Open-access field data-sharing agreements would enable model training across diverse environments that no single institution can achieve alone.

5.9 Commercial applications and current development status of UAV-based PA systems

The commercialization of UAV-based PA systems has accelerated significantly due to recent advances in AI, autonomous navigation, multispectral sensing, and VRA technologies. Agricultural UAVs are increasingly used for crop monitoring, precision spraying, irrigation management, disease detection, yield estimation, and field mapping, with precision spraying currently representing the most commercially mature application because of its operational efficiency and reduced chemical use[125,126]. Switzerland became the first country to authorize UAVs for applying plant protection products, with 11.5% of its vineyards now using drones to spray fungicides against powdery and downy mildew[158]. Since 2003, South Korea has applied UAVs in rice crop protection to combat pest threats[159].

Table 11 Representative UAV-based high-throughput phenotyping (HTP) results. H^2 = heritability; GWAS = genome-wide association study; GS = genomic selection; MT-GS = multi-trait GS

Trait	Crop	Sensor	Model	Accuracy	Breeding Use	Geography	Reference
Grain yield	Wheat	MS	MT-GS	r=0.37→0.40	Genomic selection	USA	[142]
Yield+selection	Soybean	MS	LASSO	71%-76% match	Breeder selection	USA	[143]
Leaf rolling	Rice	RGB	DCNN+GWAS	R^2=0.84-0.86	GWAS (111 loci)	China	[146]
Biomass (5)	Soybean	RGB	CNN	High R^2	Latent traits	Japan	[147]
Canopy height	Wheat	RGB SfM	Linear	H^2 comparable	Early screening	Mexico	[144]
Maturity	Soybean	RGB time-series	Sigmoid	R^2=0.82	Phenology	Belgium	[148]
Yield	Barley	RGB+MS	Ensemble	R^2=0.82	Introgression	Germany	[149]
Drought	Poplar	Thermal	VI analysis	Significant	Clonal selection	Italy	[135]

Table 12 Evidence-based examples of cross-domain UAV data integration in PA

Domains Combined	Crop	Data Sources	Key Outcome	Reference
Yield + soil + weather	Multiple	UAV MS + Sentinel-2 + ground	UAV light interception explained 78% yield variation	[150]
Yield + multi-sensor	Wheat	RGB + MS + TIR	Ensemble fusion R^2=0.69; multi-sensor outperformed single	[155]
Growth + IoT	Multiple	UAV + WSN + IoT	Consensus algorithms for data integration; real-time monitoring	[152]
Growth + satellite	Grapevine	UAV MS + satellite	DL-refined satellite NDVI better described crop status	[156]
SPAD + multi-scale	Wheat	UAV + satellite + ground	Integrated model R^2=0.926 for SPAD estimation	[151]
Weed + multi-modal	Maize	RGB+MS+TIR+SfM	Thermal improved weed mapping OA by 5%	[153]
Phenotyping + IoT	Multiple	UAV + IoT sensors	IoT-UAV on-farm automated monitoring system	[157]

According to a recent DJI Agriculture report, agricultural UAVs in China covered more than 1.052 billion hm² by 2024, supported by approximately 200 000 drones and 500 000 certified operators. Globally, the cumulative operational area of agricultural UAVs exceeded 500 million hm² by mid-2024, reflecting the rapid expansion of UAV deployment in modern agriculture[160]. However, adoption trends vary across regions because of differences in regulatory frameworks, economic conditions, and technological infrastructure.

In addition to economic benefits, UAV-assisted PA could save approximately 330 Mt of water and reduce nearly 42.6 Mt of CO_2 emissions through optimized resource management strategies[160]. Current development trends indicate that agricultural UAV systems are evolving toward greater autonomy and AI-assisted decision-making through the integration of swarm robotics, edge AI, IoT-enabled sensing platforms, and advanced communication technologies. Despite rapid commercialization, several technical, operational, economic, and regulatory limitations continue to affect the large-scale implementation of UAV-based PA systems, as discussed further in Section 6.

6 Critical challenges and limitations in agricultural UAV adoption

Despite the significant advancements and proven potential of UAVs in PA, their widespread adoption is impeded by a complex interplay of technical, economic, and regulatory hurdles. While preliminary regulations, such as those from the Civil Aviation Administration of China, are emerging, comprehensive and globally harmonized legal frameworks are still required[161]. This section critically examines the major barriers limiting the large-scale adoption and operational scalability of agricultural UAV systems (see Figure 7).

In addition to the application-specific limitations discussed in Section 5, including model transferability, limited validation across agroecological environments, interoperability challenges, and insufficient standardization of sensing protocols, broader systemic barriers continue to restrict the operational scalability and commercial deployment of UAV-based PA systems. These challenges extend beyond individual application domains and involve technical infrastructure, economic feasibility, regulatory harmonization, operational safety, and autonomous system integration. These systemic challenges persist despite the rapid commercialization and global expansion of UAV-based PA technologies discussed in Section 5.9.

6.1 Technical and operational limitations

6.1.1 Power and endurance constraints

Limited flight duration remains one of the most persistent technical challenges for UAVs. Current battery technology, primarily lithium-ion, limits heavy-lift drones (10-15 L payload) to approximately 12-16 min per charge, while lighter models may achieve up to 45 min[162]. Frequent battery replacement or recharging disrupts workflow efficiency and hinders large-scale operations. The high energy cost of flight, especially for smaller drones and during hovering, fundamentally limits mission scope and the implementation of sustained autonomous functions[163].

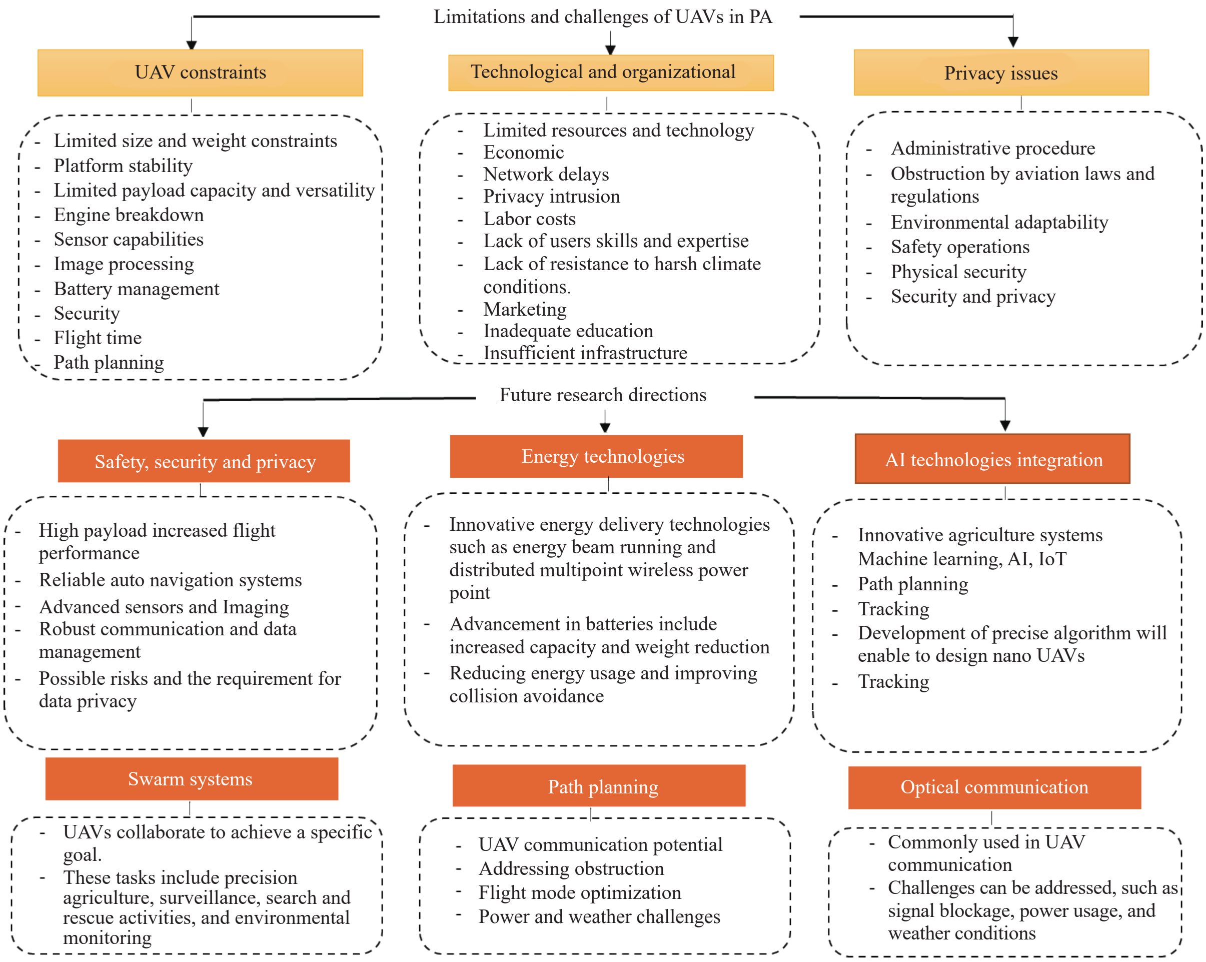

Figure 7 UAV limitations and future research directions

6.1.2 Payload capacity and platform stability

Agricultural UAV design involves balancing payload capacity, stability, and energy efficiency. Integrating large spray tanks, multispectral sensors, or LiDAR systems often compromises flight stability and increases energy consumption[163]. Limited payloads also restrict the quality and diversity of sensors deployed, directly influencing data resolution, precision, and overall mission quality in applications such as disease detection and soil analysis[52].

6.1.3 Data acquisition, processing, and management

High-resolution imaging, LiDAR, and multispectral sensors generate massive datasets that require substantial computational resources for processing. Techniques like Structure-from-Motion (SfM) and Multi-View Stereo (MVS) photogrammetry demand technical expertise and powerful hardware. Furthermore, the software for data analysis (e.g., Pix4D, ENVI, ArcGIS) often has limited functionality, high complexity, and cost, creating a barrier for farmers who lack specialized skills or resources[164]. Moreover, integrating data from heterogeneous sources (RGB, multispectral, thermal) remains problematic, causing interoperability issues and potential misinterpretations.

6.1.4 Autonomy and sensing capabilities

Despite recent advancements in autonomous navigation, true autonomy in agricultural UAV operations remains limited, as most commercial systems still require continuous human supervision, thereby restricting scalability and operational safety[164]. Achieving reliable autonomous operation requires substantial improvements in perception, sensing, collision avoidance, and intelligent path-planning systems. The development of lightweight and high-precision sensing platforms integrated with computer vision and AI is essential for real-time environmental perception and adaptive decision-making. Similarly, reliable obstacle detection using sensor fusion approaches combining LiDAR, radar, and optical imaging remains critical for safe Beyond Visual Line of Sight (BVLOS) operations, particularly in dynamic agricultural environments containing trees, power lines, and other airborne objects[164]. Furthermore, optimizing UAV flight trajectories for maximum field coverage, reduced energy consumption, and adaptive navigation under changing environmental conditions requires advanced multi-objective optimization and autonomous path-planning algorithms[165]. These limitations continue to constrain the development of fully autonomous, large-scale UAV operations in PA.

6.1.5 AI model generalization and application-specific limitations

Although ML and DL algorithms have demonstrated high predictive performance in UAV-assisted precision agriculture, their operational reliability remains highly dependent on application type, sensor configuration, environmental variability, and dataset characteristics[55]. Algorithms such as RF and SVM generally perform well for structured multispectral datasets and vegetation-index-based applications, including yield estimation and irrigation monitoring. However, these approaches often exhibit limited capability in capturing complex spatial variability and nonlinear canopy interactions across diverse field environments[53]. In contrast, DL architectures including CNNs, YOLO, and Vision Transformers provide improved spatial feature extraction and object detection performance for disease detection, weed mapping, and phenotyping applications, but require large annotated datasets, high computational resources, and extensive model training[132].

6.2 Economic and scale-related barriers

The initial capital outlay for advanced agricultural UAV systems, which can range from $15 000 to over $50 000, is prohibitive for small-scale farmers[166]. While smaller drones (DJI Mini 3 Pro) offer a lower entry point for basic monitoring, the significant economic benefits of Variable Rate Application (VRA) such as a 28% reduction in herbicide use and an 8% yield increase are primarily realized with premium, heavy-lift platforms. This creates an economic disparity[167]. For smallholders, additional barriers include the cost of operator training, lack of industry-standard protocols, and insufficient government subsidies or access to UAV-as-a-service models. The economic viability is further challenged by operational restrictions, such as the need for frequent takeoffs and landings to reload payloads[168].

6.3 Regulatory and safety hurdles

The establishment of international and national standards for UAV spraying equipment, including nozzle types, droplet size, drift measurement, and operational limits such as wind, height, and speed, is essential to ensure safe and effective operations. Regulatory bodies worldwide are actively responding to the growth of agricultural UAVs (Table 13). Landmark rulings, such as the $265 million fine levied against Bayer and BASF in the first US court case on Dicamba drift, underscore the catastrophic financial consequences of off-target chemical application. This reality elevates the requirement for technical precision and accurate spray drift prediction models from a mere operational improvement to a legally necessary mechanism for risk mitigation and environmental compliance[169].

Table 13 Comparative summary of agricultural UAV regulations

Region/ Regulatory body	Key Policy/Standard	Implementation status	Focus/Scope	Reference
USA (FAA)	Proposed Part 108 Rule (BVLOS)	Proposed (Oct 2025)	BVLOS operations <400 ft AGL; autonomous deconfliction, situational awareness, safety assurance	[171]
EU (EASA)	Predefined Risk Assessments (PDRAs)	Since Jan 2024	UAVs <150 kg; traceability, risk management, certification efficiency	[172]
Global (ISO)	ISO 23 117-1	Adopted June 2023	Design & performance verification for UAV spraying systems <150 kg	[158]
Brazil (ANAC)	Deregulation; voluntary compliance for airworthiness	Implemented 2023	Large-payload UAVs >25 kg; commercial deployment	[173]
Canada	Special Flight Operations Certificate (SFOC)	Active	UAVs >25 kg; risk assessment, operator competence	[160]
Japan (MAFF/JAAS)	Smart Agriculture Initiative; structured UAV governance	Active	Operator training, safety audits, UAV registration	[174]
South Korea	National UAV spraying programs	Active	Rice pest control; UAV tech transfer	[159]
Australia (CASA)	On-farm UAV operation; regulated BVLOS pathways	Active	Single UAVs without additional certification; BVLOS & swarm under regulation	[175]

Regulatory frameworks differ across countries, ranging from highly structured operational systems with training and safety management, to voluntary compliance schemes for large-payload drones. International standards such as ISO 23117-1[170] provide guidance on design and performance verification for UAV spraying systems, promoting interoperability and harmonization across regions.

6.4 Security and cybersecurity concerns

UAV systems are vulnerable to cyber-attacks that can target communication links, ground control stations (GCS), or onboard systems via GPS spoofing or hacking. A successful GCS attack can lead to data theft, loss of vehicle control, and mission failure. Ensuring the security and privacy of data collected by IoT-enabled UAVs requires advanced encryption and secure communication protocols, which are challenging to implement on platforms with limited computational resources[176].

7 Future research directions

The future development of UAV-assisted precision agriculture will increasingly depend on the integration of autonomous sensing systems, AI, edge computing, and interoperable digital agricultural infrastructures. Although substantial progress has been achieved in UAV-based sensing and analytical capabilities, several important research gaps remain unresolved[52,177].

One of the highest research priorities is improving the adaptability and scalability of AI-driven agricultural systems across different crops, sensor platforms, and geographic regions. Many existing UAV-based AI models remain highly dependent on localized datasets, limiting their broader applicability under variable agroecological conditions. The development of large-scale, open-access, and globally representative agricultural datasets will therefore be essential for improving model reliability and supporting cross-regional deployment[79,80].

Future research should also focus on developing application-specific AI frameworks optimized for distinct agricultural tasks rather than relying on generalized models. For example, RF and gradient-boosting approaches remain highly suitable for structured multispectral datasets and regression-based yield prediction, whereas CNN-, YOLO-, and transformer-based architectures demonstrate greater adaptability for image-intensive applications including disease detection, weed discrimination, and phenotyping. Comparative multi-environment benchmarking studies evaluating algorithm robustness, computational efficiency, annotation requirements, and cross-domain transferability remain limited and represent a major research gap in UAV-assisted precision agriculture[78].

Future research should additionally prioritize lightweight edge-AI frameworks capable of supporting real-time onboard processing and autonomous field decision-making. Current cloud-dependent analytical workflows often introduce latency, connectivity limitations, and increased computational costs. Edge-computing-enabled UAV systems may substantially improve real-time crop monitoring, autonomous navigation, and precision intervention capability under practical farming conditions[178]. Future autonomous UAV systems should also incorporate adaptive path-planning, obstacle avoidance, and weather-responsive flight-control algorithms to improve operational safety and field efficiency in dynamic agricultural environments.

Another major research direction involves the development of interoperable multi-source data fusion systems integrating UAV imagery with satellite data, IoT sensors, weather information, robotics platforms, and farm management systems. Standardized protocols for sensor calibration, image preprocessing, data annotation, and model evaluation will be essential for improving interoperability and reproducibility across different agricultural platforms and research studies[179]. Advanced drift prediction models, CFD-assisted spray simulations, and intelligent flight-management systems integrated with onboard environmental sensing may further improve spraying precision, environmental safety, and regulatory compliance under real-field operating conditions[180].

In addition, explainable AI (XAI), transfer learning, federated learning, and swarm-based multi-UAV systems are emerging as promising research areas for improving model transparency, operational scalability, and collaborative field-monitoring capability. Future studies should also emphasize economic feasibility, environmental sustainability, and adoption barriers in smallholder farming systems, particularly in underrepresented regions including Africa, South Asia, and Latin America[180]. Economically accessible UAV platforms, modular system architectures, operator training, and region-specific field validation should also be prioritized to support adoption in resource-limited agricultural systems.

Overall, future UAV-assisted precision agriculture systems are expected to evolve toward fully autonomous, intelligent, and climate-resilient agricultural ecosystems capable of supporting sustainable food production under increasingly complex environmental conditions. Future advancements should therefore prioritize not only algorithmic accuracy but also model interpretability, computational efficiency, interoperability, environmental safety, and real-world operational scalability to enable reliable large-scale deployment of UAV-assisted precision agriculture systems.

8 Conclusions

UAV-assisted PA has emerged as an advanced and effective approach for improving agricultural monitoring, field management, and resource-use efficiency. The integration of UAV platforms with advanced sensing technologies and AI-driven analytical methods has enabled rapid, high-resolution, and site-specific assessment of crop and soil conditions. Recent developments in ML and DL have further enhanced the capabilities of UAV systems for automated analysis and decision support in various applications. The reviewed literature demonstrates that combining RGB, multispectral, hyperspectral, thermal, and LiDAR sensors with intelligent analytical frameworks significantly improves monitoring accuracy, operational efficiency, and sustainability compared with conventional agricultural practices. UAV-based systems also provide greater operational flexibility and temporal resolution, enabling timely interventions that support optimized input utilization and reduced environmental impacts.

Despite substantial technological progress, several challenges continue to restrict the large-scale implementation of UAV-assisted precision agriculture. Key limitations include limited flight endurance, payload constraints, environmental sensitivity, high operational and computational costs, data-processing complexity, interoperability issues, and regulatory restrictions. In addition, many AI-based models remain highly dependent on crop-specific and region-specific datasets, limiting their robustness and transferability across diverse agricultural environments. The absence of standardized protocols for sensor calibration, data preprocessing, information fusion, and model evaluation also remains a major obstacle for system interoperability and commercial scalability.

Future research is expected to focus on the development of autonomous, intelligent, and interconnected agricultural ecosystems through the integration of edge computing, explainable AI (XAI), IoT technologies, cloud-based analytics, swarm robotics, and real-time decision-support systems. Advancements in autonomous navigation, communication infrastructure, multisource data fusion, and generalized AI frameworks will be essential for improving the scalability, reliability, and affordability of UAV technologies, particularly for smallholder and resource-limited farming systems. Continued interdisciplinary collaboration among agricultural scientists, engineers, computer scientists, and policymakers will play a critical role in accelerating the adoption of sustainable and climate-resilient UAV-enabled precision agriculture worldwide.

Acknowledgements

National Key R&D Program of China (2023YFD2000200); Ningxia Key Research and Development Plan (2023BCF01051); National Natural Science Foundation of China (32302410).

[References]

[1] Guebsi R, Mami S, Chokmani K. Drones in precision agriculture: A comprehensive review of applications, technologies, and challenges. Drones, 2024; 8(11): 686.

[2] Kaousar R, Wang G, Aslan M F, Shan C, Wang B, Yan Y, et al. Study on spray droplet drift and deposition characteristics under different nozzles and environmental conditions for knapsack and boom sprayers. Archives of Agronomy and Soil Science, 2026; 72(1): 1–18.

[3] Karunathilake E, Le A T, Heo S, Chung Y S, Mansoor S. The path to smart farming: Innovations and opportunities in precision agriculture. Agriculture, 2023; 13(8): 1593.

[4] Abdulraheem M I, Khan N. Precision agriculture: Towards emerging trends in food security and sustainability. Advances in Agricultural Technology & Plant Sciences, 2023; 6(1): 1–4.

[5] ISPA. Precision agriculture definition, 2024. Available: https://www.ispag.org/about/definition.

[6] Mansoor S, Iqbal S, Popescu S M, Kim S L, Chung Y S, Baek J-H. Integration of smart sensors and IoT in precision agriculture: trends, challenges and future prospectives. Frontiers in Plant Science, 2025; 16: 1587869.

[7] Miller T, Mikiciuk G, Durlik I, Mikiciuk M, Łobodzińska A, Śnieg M. The IoT and AI in agriculture: The time is now—A systematic review of smart sensing technologies. Sensors, 2025; 25(12): 3583.

[8] Sudha S, Loret J. A review on machine learning-based precision agriculture techniques for crop farming monitoring with IoT. Discover Environment, 2026; 4(1): 10.

[9] Zhang S, Wang X, Lin H, Qiang Z. A review of the application of UAV multispectral remote sensing technology in precision agriculture. Smart Agricultural Technology, 2025; 12: 101406.

[10] Alotaibi A, Chatwin C, Birch P. Evaluating global navigation satellite system (GNSS) constellation performance for unmanned aerial vehicle (UAV) Navigation Precision. Journal of Computer and Communications, 2024; 12(9): 39–62.

[11] Gómez Á L P, Del Olmo J J L, López-de-Teruel P E, Ruiz A, Clemente F J G, Bueno A C. MeloDI: An internet of things architecture to evaluate melon quality by means of machine learning using sensors data and drone images. IEEE Access, 2024; 12: 193831–193847.

[12] Padhiary M, Kumar A, Sethi L N. Emerging technologies for smart and sustainable precision agriculture. Discover Robotics, 2025; 1(1): 6.

[13] Senoo E E K, Anggraini L, Kumi J A, Karolina L B, Akansah E, Sulyman H A, et al. IoT solutions with artificial intelligence technologies for precision agriculture: definitions, applications, challenges, and opportunities. Electronics, 2024; 13(10): 1894.

[14] Xie W Y, Wang H, Liu W P, Zang H C. Early-stage pine wilt disease detection via multi-feature fusion in UAV imagery. Forests, 2024; 15(1): 171.

[15] Imran, Li J. Technological advances in UAV-assisted crop monitoring. uav aerodynamics and crop interaction. Revolutionizing Modern Agriculture with Drone, 2025; pp.237–275. DOI: 10.1007/978-981-96-

8402-1_8.

[16] Vashishth T K, Sharma V, Sharma K K, Kumar B, Chaudhary S, Ahamad S. Unmanned aircraft systems (UASs) technology, applications, and challenges. Unmanned Aircraft Systems, 2024: 1–63. DOI: 10.1002/9781394230648.ch1.

[17] Manfreda S, Dor E B. Remote sensing of the environment using unmanned aerial systems. Unmanned Aerial Systems for Monitoring Soil, Vegetation, and Riverine Environments, 2023; 3–36. DOI: 10.1016/B978-0-323-85283-8.00009-6.

[18] Mira-García A B, Romero-Trigueros C, Gambín J M B, del Puerto Sánchez-Iglesias M, Tortosa P A N, Nicolás E N. Estimation of stomatal conductance by infra-red thermometry in citrus trees cultivated under regulated deficit irrigation and reclaimed water. Agricultural Water Management, 2023; 276: 108057.

[19] Velusamy P, Rajendran S, Mahendran R K, Naseer S, Shafiq M, Choi J-G. Unmanned aerial vehicles (UAV) in precision agriculture: Applications and challenges. Energies, 2021; 15(1): 217.

[20] Prudden S L. Rotor aerodynamic interaction effects for multirotor unmanned aircraft systems in forward flight: RMIT University; 2020. DOI: 10.25439/rmt.27598599

[21] Mohsan S A H, Khan M A, Noor F, Ullah I, Alsharif M H. Towards the unmanned aerial vehicles (UAVs): A comprehensive review. Drones, 2022; 6(6): 147.

[22] Saeed A S, Younes A B, Cai C, Cai G. A survey of hybrid unmanned aerial vehicles. Progress in Aerospace Sciences, 2018; 98: 91–105.

[23] Allred B, Eash N, Freeland R, Martinez L, Wishart D. Effective and efficient agricultural drainage pipe mapping with UAS thermal infrared imagery: A case study. Agricultural Water Management, 2018; 197: 132–137.

[24] Gašparović M, Zrinjski M, Barković Đ, Radočaj D. An automatic method for weed mapping in oat fields based on UAV imagery. Computers and Electronics in Agriculture, 2020; 173: 105385.

[25] Freitas H, Faiçal BS, e Silva A V C, Ueyama J. Use of UAVs for an efficient capsule distribution and smart path planning for biological pest control. Computers and Electronics in Agriculture, 2020; 173: 105387.

[26] Wu B Z, Liang A J, Zhang H F, Zhu T F, Zou Z Y, Yang D M, et al. Application of conventional UAV-based high-throughput object detection to the early diagnosis of pine wilt disease by deep learning. Forest Ecology and Management, 2021; 486: 118986.

[27] Moriya É A S, Imai N N, Tommaselli A M G, Berveglieri A, Santos GH, Soares M A, et al. Detection and mapping of trees infected with citrus gummosis using UAV hyperspectral data. Computers and Electronics in Agriculture, 2021; 188: 106298.

[28] Ishengoma F S, Rai I A, Said R N. Identification of maize leaves infected by fall armyworms using UAV-based imagery and convolutional neural networks. Computers and Electronics in Agriculture, 2021; 184: 106124.

[29] Lane P, Throneberry G, Fernandez I, Hassanalian M, Vasconcellos R, Abdelkefi A. Towards bio-inspiration, development, and manufacturing of a flapping-wing micro air vehicle. Drones, 2020; 4(3): 39.

[30] Zhou M, Zhou Z, Liu L, Huang J, Lyu Z. Review of vertical take-off and landing fixed-wing UAV and its application prospect in precision agriculture. International Journal of Precision Agricultural Aviation, 2020; 3(4): 8-17.

[31] 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 Sensing, 2021; 13(6): 1204.

[32] Radoglou-Grammatikis P, Sarigiannidis P, Lagkas T, Moscholios I. A compilation of UAV applications for precision agriculture. Computer Networks, 2020; 172: 107148.

[33] Lu N, Zhou J, Han Z, Li D, Cao Q, Yao X, et al. Improved estimation of aboveground biomass in wheat from RGB imagery and point cloud data acquired with a low-cost unmanned aerial vehicle system. Plant Methods, 2019; 15(1): 17.

[34] Maes W H, Stepp K. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. Trends in Plant Science, 2019; 24(2): 152–164.

[35] Daniels L, Eeckhout E, Wieme J, Dejaegher Y, Audenaert K, Maes W H. Identifying the optimal radiometric calibration method for UAV-based multispectral imaging. Remote Sensing, 2023; 15(11): 2909.

[36] Park S, Ryu D, Fuentes S, Chung H, Hernández-Montes E, O'Connell M. Adaptive estimation of crop water stress in nectarine and peach orchards using high-resolution imagery from an unmanned aerial vehicle (UAV). Remote Sensing, 2017; 9(8): 828.

[37] Khuzaimah Z, Nawi N M, Adam S N, Kalantar B, Emeka O J, Ueda N. Application and potential of drone technology in oil palm plantation: Potential and limitations. Journal of Sensors, 2022. DOI: 10.1155/2022/5385505.

[38] Mohsan S A H, Othman N Q H, Li Y, Alsharif M H, Khan M A. Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. Intelligent Service Robotics, 2023; 16(1): 109–137.

[39] de Oca A M, Flores G. The AgriQ: A low-cost unmanned aerial system for precision agriculture. Expert Systems with Applications, 2021; 182: 115163.

[40] Tsouros D C, Terzi A, Bibi S, Vakouftsi F, Pantzios V. Towards a fully open-source system for monitoring of crops with UAVs in precision agriculture. Proceedings of the 24th Pan-Hellenic Conference on Informatics, 2020; pp.322–326. DOI: 10.1145/3437120.3437333.

[41] Näsi R, Viljanen N, Kaivosoja J, Alhonoja K, Hakala T, Markelin L, et al. Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features. Remote Sensing, 2018; 10(7): 1082.

[42] Pathak R, Barzin R, Bora G C. Data-driven precision agricultural applications using field sensors and Unmanned Aerial Vehicle. International Journal of Precision Agricultural Aviation, 2018; 1(1). DOI: 10.33440/j.ijpaa.20180101.0004.

[43] Mateen A, Zhu Q. Weed detection in wheat crop using UAV for precision agriculture. Pak J Agric Sci, 2019; 56: 809–817.

[44] Bollas N, Kokinou E, Polychronos V. Comparison of sentinel-2 and UAV multispectral data for use in precision agriculture: An application from northern Greece. Drones, 2021; 5(2): 35.

[45] Di Gennaro S F, Toscano P, Gatti M, Poni S, Berton A, Matese A. Spectral comparison of UAV-based hyper and multispectral cameras for precision viticulture. Remote Sensing, 2022; 14(3): 449.

[46] Sousa J J, Toscano P, Matese A, Di Gennaro S F, Berton A, Gatti M, et al. UAV-based hyperspectral monitoring using push-broom and snapshot sensors: A multisite assessment for precision viticulture applications. Sensors, 2022; 22(17): 6574.

[47] Wang Y, Yang Z, Khan H A, Kootstra G. Improving radiometric block adjustment for UAV multispectral imagery under variable illumination conditions. Remote Sensing, 2024; 16(16): 3019.

[48] Dokania N K, Yadav S S, editors. Feature extraction techniques in agriculture with stressed vegetation: A review. 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), IEEE, 2022. DOI: 10.1109/ICAC3N56670.2022.10074479.

[49] Csillik O, Cherbini J, Johnson R, Lyons A, Kelly M. Identification of citrus trees from unmanned aerial vehicle imagery using convolutional neural networks. Drones, 2018; 2(4): 39.

[50] Barriguinha A, de Castro Neto M, Gil A. Vineyard yield estimation, prediction, and forecasting: A systematic literature review. Agronomy, 2021; 11(9): 1789.

[51] Bongomin O, Lamo J, Guina J M, Okello C, Ocen G G, Obura M, et al. UAV image acquisition and processing for high-throughput phenotyping in agricultural research and breeding programs. The Plant Phenome Journal, 2024; 7(1). DOI: 10.1002/ppj2.20096.

[52] Agrawal J, Arafat M Y. Transforming farming: A review of AI-powered UAV technologies in precision agriculture. Drones, 2024; 8(11): 664.

[53] Jin X L, McCabe M, Diao C Y, Li Z H, Yin D M. Remote sensing application for precision agriculture. Frontiers in Plant Science, 2023. DOI: 10.3389/978-2-8325-3182-2.

[54] Ponnusamy V, Natarajan S. Precision agriculture using advanced technology of IoT, unmanned aerial vehicle, augmented reality, and machine learning. Smart Sensors for Industrial Internet of Things: Challenges, Solutions and Applications, 2021; pp.207–229. DOI:10.1007/978-3-030-52624-5_14.

[55] Shammi S A, Huang Y, Feng G, Tewolde H, Zhang X, Jenkins J, et al. Application of UAV multispectral imaging to monitor soybean growth with yield prediction through machine learning. Agronomy, 2024; 14(4): 672.

[56] Liakos K G, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: A review. Sensors, 2018; 18(8): 2674.

[57] Zhang S, Li X, Ba Y, Lyu X, Zhang M, Li M. Banana fusarium wilt disease detection by supervised and unsupervised methods from UAV-

based multispectral imagery. Remote Sensing, 2022; 14(5): 1231.
[58] Romero M, Luo Y C, Su B F, Fuentes S. Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management. Computers and Electronics in Agriculture, 2018; 147: 109–117.
[59] Che'Ya N N, Dunwoody E, Gupta M. Assessment of weed classification using hyperspectral reflectance and optimal multispectral UAV imagery. Agronomy, 2021; 11(7): 1435.
[60] Zheng C, Abd-Elrahman A, Whitaker V. Remote sensing and machine learning in crop phenotyping and management, with an emphasis on applications in strawberry farming. Remote Sensing, 2021; 13(3): 531.
[61] Su J Y, Yi D W, Su B F, Mi Z W, Liu C J, Hu X P, et al. Aerial visual perception in smart farming: Field study of wheat yellow rust monitoring. IEEE Transactions on Industrial Informatics, 2020; 17(3): 2242–2249.
[62] Maimaitijiang M, Sagan V, Sidike P, Hartling S, Esposito F, Fritschi F B. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sensing of Environment, 2020; 237: 111599.
[63] Darwin B, Dharmaraj P, Prince S, Popescu D E, Hemanth D J. Recognition of bloom/yield in crop images using deep learning models for smart agriculture: A review. Agronomy, 2021; 11(4): 646.
[64] Alves A N, Souza W S, Borges D L. Cotton pests classification in field-based images using deep residual networks. Computers and Electronics in Agriculture, 2020; 174: 105488.
[65] Wang C, Chen Y, Xiao Z, Zeng X, Tang S, Lin F, et al. Cotton blight identification with ground framed canopy photo-assisted multispectral UAV images. Agronomy, 2023; 13(5): 1222.
[66] Garza B N, Ancona V, Enciso J, Perotto-Baldivieso HL, Kunta M, Simpson C. Quantifying citrus tree health using true color UAV images. Remote Sensing, 2020; 12(1): 170.
[67] Schirrmann M, Giebel A, Gleiniger F, Pflanz M, Lentschke J, Dammer K-H. Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery. Remote Sensing, 2016; 8(9): 706.
[68] Apolo-Apolo O, Martínez-Guanter J, Egea G, Raja P, Pérez-Ruiz M. Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV. European Journal of Agronomy, 2020; 115: 126030.
[69] Apolo-Apolo O E, Pérez-Ruiz M, Martinez-Guanter J, Valente J. A cloud-based environment for generating yield estimation maps from apple orchards using UAV imagery and a deep learning technique. Frontiers in Plant Science, 2020; 11: 1086.
[70] Liu Z J, Guo P J, Liu H, Fan P, Zeng P Z, Liu X Y, et al. Gradient boosting estimation of the leaf area index of apple orchards in UAV remote sensing. Remote Sensing, 2021; 13(16): 3263.
[71] Chandel A K, Khot L R, Sallato B. Apple powdery mildew infestation detection and mapping using high-resolution visible and multispectral aerial imaging technique. Scientia Horticulturae, 2021; 287: 110228.
[72] Altalak M, Ammad uddin M, Alajmi A, Rizg A. Smart agriculture applications using deep learning technologies: A survey. Applied Sciences, 2022; 12(12): 5919.
[73] Aslan M F, Durdu A, Sabanci K, Ropelewska E, Gültekin S S. A comprehensive survey of the recent studies with UAV for precision agriculture in open fields and greenhouses. Applied Sciences, 2022; 12(3): 1047.
[74] Borah J, Singh H K, Sarmah K, editors. Automatic detection of diseases from chest radiographs using image augmentations and deep convolutional neural networks. 2023 4th International Conference on Computing and Communication Systems (I3CS), IEEE, 2023. DOI: 10.1109/I3CS58314.2023.10127248.
[75] Khan A, Vibhute A D, Mali S, Patil C H. A systematic review on hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications. Ecological Informatics, 2022; 69: 101678.
[76] Jeong S, Ko J, Kim M, Kim J. Construction of an unmanned aerial vehicle remote sensing system for crop monitoring. Journal of Applied Remote Sensing, 2016; 10(2): 026027–026027.
[77] Pandey A, Jain K. An intelligent system for crop identification and classification from UAV images using conjugated dense convolutional neural network. Computers and Electronics in Agriculture, 2022; 192: 106543.
[78] El Sakka M, Ivanovici M, Chaari L, Mothe J. A review of CNN applications in smart agriculture using multimodal data. Sensors, 2025; 25(2): 472.
[79] Phang S K, Chiang T H A, Happonen A, Chang M M L. From satellite to UAV-based remote sensing: A review on precision agriculture. IEEE Access, 2023. DOI: 10.1109/ACCESS.2023.3330886.
[80] Paul N, Sunil G, Horvath D, Sun X. Deep learning for plant stress detection: A comprehensive review of technologies, challenges, and future directions. Computers and Electronics in Agriculture, 2025; 229: 109734.
[81] Fu Z, Jiang J, Gao Y, Krienke B, Wang M, Zhong K, et al. Wheat growth monitoring and yield estimation based on multi-rotor unmanned aerial vehicle. Remote Sensing, 2020; 12(3): 508.
[82] Yang B, Zhu W, Rezaei E E, Li J, Sun Z, Zhang J. The optimal phenological phase of maize for yield prediction with high-frequency UAV remote sensing. Remote Sensing, 2022; 14(7): 1559.
[83] Wan L, Cen H, Zhu J, Zhang J, Zhu Y, Sun D, et al. Grain yield prediction of rice using multi-temporal UAV-based RGB and multispectral images and model transfer–a case study of small farmlands in the South of China. Agricultural and Forest Meteorology, 2020; 291: 108096.
[84] Sarron J, Malézieux É, Sané C A B, Faye É. Mango yield mapping at the orchard scale based on tree structure and land cover assessed by UAV. Remote Sensing, 2018; 10(12): 1900.
[85] Killeen P, Kiringa I, Yeap T, Branco P. Corn grain yield prediction using UAV-based high spatiotemporal resolution imagery, machine learning, and spatial cross-validation. Remote Sensing, 2024; 16(4): 683.
[86] Priyatikanto R, Lu Y, Dash J, Sheffield J. Improving generalisability and transferability of machine-learning-based maize yield prediction model through domain adaptation. Agricultural and Forest Meteorology, 2023; 341: 109652.
[87] Khaki S, Wang L, Archontoulis S V. A CNN-RNN framework for crop yield prediction. Frontiers in Plant Science, 2020; 10: 1750.
[88] Guo Y, Xiao Y, Hao F, Zhang X, Chen J, de Beurs K, et al. Comparison of different machine learning algorithms for predicting maize grain yield using UAV-based hyperspectral images. International Journal of Applied Earth Observation and Geoinformation, 2023; 124: 103528.
[89] Abdulridha J, Ampatzidis Y, Kakarla S C, Roberts P. Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. Precision Agriculture, 2020; 21(5): 955–978.
[90] Shi Y, Han L, Kleerekoper A, Chang S, Hu T. Novel cropdocnet model for automated potato late blight disease detection from unmanned aerial vehicle-based hyperspectral imagery. Remote Sensing, 2022; 14(02): 396.
[91] Nguyen C, Sagan V, Skobalski J, Severo J I. Early detection of wheat yellow rust disease and its impact on terminal yield with multi-spectral UAV-imagery. Remote Sensing, 2023; 15(13): 3301.
[92] Iost Filho F H, Heldens W B, Kong Z, De Lange E S. Drones: innovative technology for use in precision pest management. Journal of Economic Entomology, 2020; 113(1): 1–25.
[93] Yu G, Ma B, Zhang R, Xu Y, Lian Y, Dong F. CPD-YOLO: A cross-platform detection method for cotton pests and diseases using UAV and smartphone imaging. Industrial Crops and Products, 2025; 234: 121515.
[94] Yu R, Huo L, Huang H, Yuan Y, Gao B, Liu Y, et al. Early detection of pine wilt disease tree candidates using time-series of spectral signatures. Frontiers in Plant Science, 2022; 13: 1000093.
[95] Narmilan A, Gonzalez F, Salgadoe A S A, Powell K. Detection of white leaf disease in sugarcane using machine learning techniques over UAV multispectral images. Drones, 2022; 6(9): 230.
[96] Zhang X, Han L, Dong Y, Shi Y, Huang W, Han L, et al. A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images. Remote Sensing, 2019; 11(13): 1554.
[97] Abdulridha J, Min A, Rouse M N, Kianian S, Isler V, Yang C. Evaluation of stem rust disease in wheat fields by drone hyperspectral imaging. Sensors, 2023; 23(8): 4154.
[98] Ualiyeva R M, Kaverina M M, Osipova A V, Kairbayev Y B, Zhangazin S B, Iksat N N, et al. VNIR hyperspectral signatures for early detection and machine-learning classification of wheat diseases. Plants, 2025; 14(23): 3644.
[99] Mahmood A, Anwar W, Sattar H, Hassan S R, Sheraz M, Chuah T C. Deep learning framework using UAV imagery for multi-disease detection in cereal crops. Scientific Reports, 2025; 16(1): 3339-3339.
[100] Selvaraj M G, Vergara A, Montenegro F, Ruiz H A, Safari N, Raymaekers D, et al. Detection of banana plants and their major diseases through aerial images and machine learning methods: A case study in DR

Congo and Republic of Benin. ISPRS Journal of Photogrammetry and Remote Sensing, 2020; 169: 110–124.

[101] Huang Z Y, Bai X L, Gouda M, Hu H, Yang N Y, He Y, et al. Transfer learning for plant disease detection model based on low-altitude UAV remote sensing. Precision Agriculture, 2025; 26(1): 15.

[102] Deng X L, Zhu Z H, Yang J C, Zheng Z X, Huang Z, Yin X B, et al. Detection of citrus huanglongbing based on multi-input neural network model of UAV hyperspectral remote sensing. Remote Sensing, 2020; 12(17): 2678.

[103] 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.

[104] Zhou J P, Xu Y P, Gu X H, Chen T E, Sun Q, Zhang S, et al. High-precision mapping of soil organic matter based on UAV imagery using machine learning algorithms. Drones, 2023; 7(5): 290.

[105] Heil J, Jörges C, Stumpe B. Fine-scale mapping of soil organic matter in agricultural soils using UAVs and machine learning. Remote Sensing, 2022; 14(14): 3349.

[106] Zhu W, Rezaei E E, Nouri H, Yang T, Li B, Gong H, et al. Quick detection of field-scale soil comprehensive attributes via the integration of UAV and sentinel-2B remote sensing data. Remote Sensing, 2021; 13(22): 4716.

[107] El-Jamaoui I, Delgado-Iniesta M J, Martínez Sánchez M J, Pérez Sirvent C, Martínez López S. Assessing soil organic carbon in semi-arid agricultural soils using UAVs and machine learning: A pathway to sustainable water and soil resource management. Sustainability, 2025; 17(8): 3440.

[108] Song Q, Gao X H, Song Y T, Li Q L, Chen Z, Li R X, et al. Estimation and mapping of soil texture content based on unmanned aerial vehicle hyperspectral imaging. Scientific Reports, 2023; 13(1): 14097.

[109] Guan Y, Grote K, Schott J, Leverett K. Prediction of soil water content and electrical conductivity using random forest methods with UAV multispectral and ground-coupled geophysical data. Remote Sensing, 2022; 14(4): 1023.

[110] Vavlas N-C, Porre R, Meng L, Elhakeem A, van Egmond F, Kooistra L, et al. Cover crop impacts on soil organic matter dynamics and its quantification using UAV and proximal sensing. Smart Agricultural Technology, 2024; 9: 100621.

[111] Biney J K M, Houška J, Volánek J, Abebrese D K, Cervenka J. Examining the influence of bare soil UAV imagery combined with auxiliary datasets to estimate and map soil organic carbon distribution in an erosion-prone agricultural field. Science of the Total Environment, 2023; 870: 161973.

[112] Yang X Y, Bao N S, Li W W, Liu S J, Fu Y H, Mao Y C. Soil nutrient estimation and mapping in farmland based on UAV imaging spectrometry. Sensors, 2021; 21(11): 3919.

[113] Bah M D, Hafiane A, Canals R. Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Remote Sensing, 2018; 10(11): 1690.

[114] De Castro A I, Torres-Sánchez J, Peña J M, Jiménez-Brenes F M, Csillik O, López-Granados F. An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery. Remote Sensing, 2018; 10(2): 285.

[115] Rosle R, Che'Ya N N, Rahmat F, Sulaiman N S, Zakaria N-I, Berahim Z, et al. Deep learning-based temporal change detection of broadleaved weed infestation in rice fields using UAV multispectral imagery. Frontiers in Plant Science, 2025; 16: 1655391.

[116] Mesías-Ruiz G A, Borra-Serrano I, Dorado J, de Castro A I, Peña J M. Multispecies weed mapping using deep learning on UAV imagery for SSWM in maize and tomato. Precision Agriculture, 2026; 27(1): 9.

[117] Gallo I, Rehman A U, Dehkordi R H, Landro N, La Grassa R, Boschetti M. Deep object detection of crop weeds: Performance of YOLOv7 on a real case dataset from UAV images. Remote Sensing, 2023; 15(2): 539.

[118] Reedha R, Dericquebourg E, Canals R, Hafiane A. Vision transformers for weeds and crops classification of high resolution UAV images. arXiv preprint arXiv: 210902716, 2021.

[119] Anderegg J, Tschurr F, Kirchgessner N, Treier S, Schmucki M, Streit B, et al. On-farm evaluation of UAV-based aerial imagery for season-long weed monitoring under contrasting management and pedoclimatic conditions in wheat. Computers and Electronics in Agriculture, 2023; 204: 107558.

[120] Mwitta C, Rains G C, Prostko E. Evaluation of inference performance of deep learning models for real-time weed detection in an embedded computer. Sensors, 2024; 24(2): 514.

[121] Guo S, Li J, Yao W, Zhan Y, Li Y, Shi Y. Distribution characteristics on droplet deposition of wind field vortex formed by multi-rotor UAV. PloS one, 2019; 14(7): e0220024.

[122] Wang C, Wongsuk S, Huang Z, Yu C, Han L, Zhang J, et al. Comparison between drift test bench and other techniques in spray drift evaluation of an eight-rotor unmanned aerial spraying system: the influence of meteorological parameters and nozzle types. Agronomy, 2023; 13(1): 270.

[123] Chen S, Lan Y, Zhou Z, Ouyang F, Wang G, Huang X, et al. Effect of droplet size parameters on droplet deposition and drift of aerial spraying by using plant protection UAV. Agronomy, 2020; 10(2): 195.

[124] Paul RAI, Arthanari PM, Peramaiyan P, Kumar V, Bagavathiannan M, Surya K. Comparative analysis of UAV and electric backpack sprayers for herbicide efficacy and crop-weed nutrient dynamics in direct-seeded rice. Journal of Agriculture and Food Research, 2025: 102307. DOI: 10.1016/j.jafr.2025.102307.

[125] Cavalaris C, Karamoutis C, Markinos A. Efficacy of cotton harvest aids applications with unmanned aerial vehicles (UAV) and ground-based field sprayers–A case study comparison. Smart Agricultural Technology, 2022; 2: 100047.

[126] Biglia A, Grella M, Bloise N, Comba L, Mozzanini E, Sopegno A, et al. UAV-spray application in vineyards: Flight modes and spray system adjustment effects on canopy deposit, coverage, and off-target losses. Science of the total environment, 2022; 845: 157292.

[127] Seo Y, Umeda S, Yoshikawa N. Environmental impact of agricultural sprayers used in Japanese rice farming. International Journal of Agricultural Sustainability, 2023; 21(1): 2247803.

[128] Safaeinejad M, Ghasemi-Nejad-Raeini M, Taki M. Reducing energy and environmental footprint in agriculture: A study on drone spraying vs. conventional methods. Plos one, 2025; 20(6): e0323779.

[129] Li L, Hu Z, Liu Q, Yi T, Han P, Zhang R, et al. Effect of flight velocity on droplet deposition and drift of combined pesticides sprayed using an unmanned aerial vehicle sprayer in a peach orchard. Frontiers in Plant Science, 2022; 13: 981494.

[130] Ni M, Wang H, Liu X, Liao Y, Fu L, Wu Q, et al. Design of variable spray system for plant protection UAV based on CFD simulation and regression analysis. Sensors, 2021; 21(2): 638.

[131] Bian J, Zhang Z, Chen J, Chen H, Cui C, Li X, et al. Simplified evaluation of cotton water stress using high resolution unmanned aerial vehicle thermal imagery. Remote Sensing, 2019; 11(3): 267.

[132] Wang J, Lou Y, Wang W, Liu S, Zhang H, Hui X, et al. A robust model for diagnosing water stress of winter wheat by combining UAV multispectral and thermal remote sensing. Agricultural Water Management, 2024; 291: 108616.

[133] Brewer K, Clulow A, Sibanda M, Gokool S, Odindi J, Mutanga O, et al. Estimation of maize foliar temperature and stomatal conductance as indicators of water stress based on optical and thermal imagery acquired using an unmanned aerial vehicle (UAV) platform. Drones, 2022; 6(7): 169.

[134] Kapari M, Sibanda M, Magidi J, Mabhaudhi T, Nhamo L, Mpandeli S. Comparing machine learning algorithms for estimating the maize crop water stress index (CWSI) using UAV-acquired remotely sensed data in smallholder croplands. Drones, 2024; 8(2): 61.

[135] Ludovisi R, Tauro F, Salvati R, Khoury S, Mugnozza Scarascia G, Harfouche A. UAV-based thermal imaging for high-throughput field phenotyping of black poplar response to drought. Frontiers in Plant Science, 2017; 8: 1681.

[136] Ndlovu H S, Odindi J, Sibanda M, Mutanga O, Clulow A, Chimonyo V G, et al. A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (UAV)-based proximal and remotely sensed data. Remote Sensing, 2021; 13(20): 4091.

[137] Lacerda L N, Snider J L, Cohen Y, Liakos V, Gobbo S, Vellidis G. Using UAV-based thermal imagery to detect crop water status variability in cotton. Smart Agricultural Technology, 2022; 2: 100029.

[138] Matese A, Baraldi R, Berton A, Cesaraccio C, Di Gennaro S F, Duce P, et al. Estimation of water stress in grapevines using proximal and remote sensing methods. Remote Sensing, 2018; 10(1): 114.

[139] Shi Y, Thomasson J A, Murray S C, Pugh N A, Rooney W L, Shafian S, et al. Unmanned aerial vehicles for high-throughput phenotyping and

agronomic research. PloS one, 2016; 11(7): e0159781.
[140] Haghighattalab A, González Pérez L, Mondal S, Singh D, Schinstock D, Rutkoski J, et al. Application of unmanned aerial systems for high throughput phenotyping of large wheat breeding nurseries. Plant Methods, 2016; 12(1): 35.
[141] Tattaris M, Reynolds M P, Chapman S C. A direct comparison of remote sensing approaches for high-throughput phenotyping in plant breeding. Frontiers in Plant Science, 2016; 7: 1131.
[142] Kaushal S, Gill H S, Billah M M, Khan S N, Halder J, Bernardo A, et al. Enhancing the potential of phenomic and genomic prediction in winter wheat breeding using high-throughput phenotyping and deep learning. Frontiers in Plant Science, 2024; 15: 1410249.
[143] Zhou J, Beche E, Vieira C C, Yungbluth D, Zhou J, Scaboo A, et al. Improve soybean variety selection accuracy using UAV-based high-throughput phenotyping technology. Frontiers in Plant Science, 2022; 12: 768742.
[144] Volpato L, Pinto F, González-Pérez L, Thompson I G, Borém A, Reynolds M, et al. High throughput field phenotyping for plant height using UAV-based RGB imagery in wheat breeding lines: Feasibility and validation. Frontiers in Plant Science, 2021; 12: 591587.
[145] Alves A K, Araújo M S, Chaves S F, Dias L A S, Corrêdo L P, Pessoa G G, et al. High throughput phenotyping in soybean breeding using RGB image vegetation indices based on drone. Scientific Reports, 2024; 14(1): 32055.
[146] Jiang Z, Tu H, Bai B, Yang C, Zhao B, Guo Z, et al. Combining UAV - RGB high - throughput field phenotyping and genome - wide association study to reveal genetic variation of rice germplasms in dynamic response to drought stress. New Phytologist, 2021; 232(1): 440–455.
[147] Okada M, Barras C, Toda Y, Hamazaki K, Ohmori Y, Yamasaki Y, et al. High-throughput phenotyping of soybean biomass: conventional trait estimation and novel latent feature extraction using UAV remote sensing and deep learning models. Plant Phenomics, 2024; 6: 0244.
[148] Borra-Serrano I, De Swaef T, Quataert P, Aper J, Saleem A, Saeys W, et al. Closing the phenotyping gap: High resolution UAV time series for soybean growth analysis provides objective data from field trials. Remote Sensing, 2020; 12(10): 1644.
[149] Herzig P, Borrmann P, Knauer U, Klück H-C, Kilias D, Seiffert U, et al. Evaluation of RGB and multispectral unmanned aerial vehicle (UAV) imagery for high-throughput phenotyping and yield prediction in barley breeding. Remote Sensing, 2021; 13(14): 2670-2670
[150] Schut A G T, Traore P C S, Blaes X, de By R A. Assessing yield and fertilizer response in heterogeneous smallholder fields with UAVs and satellites. Field Crops Research, 2018; 221: 98–107.
[151] Zhang S, Zhao G, Lang K, Su B, Chen X, Xi X, et al. Integrated satellite, unmanned aerial vehicle (UAV) and ground inversion of the SPAD of winter wheat in the reviving stage. Sensors, 2019; 19(7): 1485.
[152] Popescu D, Stoican F, Stamatescu G, Ichim L, Dragana C. Advanced UAV–WSN system for intelligent monitoring in precision agriculture. Sensors, 2020; 20(3): 817.
[153] Xu B Y, Meng R, Chen G S, Liang L L, Lv Z G, Zhou L F, et al. Improved weed mapping in corn fields by combining UAV - based spectral, textural, structural, and thermal measurements. Pest Management Science, 2023; 79(7): 2591–2602.
[154] Pretto A, Aravecchia S, Burgard W, Chebrolu N, Dornhege C, Falck T, et al. Building an aerial–ground robotics system for precision farming: an adaptable solution. IEEE Robotics & Automation Magazine, 2020; 28(3): 29–49.
[155] Fei S, Hassan M A, Xiao Y, Su X, Chen Z, Cheng Q, et al. UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat. Precision agriculture, 2023; 24(1): 187–212.
[156] Mazzia V, Comba L, Khaliq A, Chiaberge M, Gay P. UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture. Sensors, 2020; 20(9): 2530.
[157] Almalki F, Soufiene B, Alsamhi S H, Sakli H. A low-cost platform for environmental smart farming monitoring system based on IoT and UAVs. Sustainability, 2021; 13(11): 5908.
[158] Anken T, Coupy G, Dubuis P H, Favre G, Geiser H C, Gurba A, et al. Plant protection treatments in Switzerland using unmanned aerial vehicles: regulatory framework and lessons learned. Pest Management Science, 2025; 81(7): 3419-3429.
[159] Baek J, Eun., Kim S, Lee Y, Jeong M, Han X, et al. Reduction of pesticide dosage and off-target drift with enhanced control efficacy in unmanned aerial vehicle-based application using lecithin adjuvants. Pest Management Science, 2024. DOI: 10.1002/ps.8551.
[160] DJI Agriculture. Agricultural drone industry insight report, 2024.
[161] Zając G K. Safety regulation in international aviation law: Normative aspects of safety: Taylor & Francis; 2025. DOI: 10.4324/9781003557876.
[162] Imran, Li J. UAV design for agricultural applications. UAV aerodynamics and crop interaction: Revolutionizing modern agriculture with drone. Springer; 2025. pp.169-202. DOI: 10.1007/978-981-96-8402-1_6.
[163] Acar O, Honkavaara E, Botez R M, Bayburt D Ç. Mechanisms and control strategies for morphing structures in quadrotors: A review and future prospects. Drones, 2025; 9(9): 663.
[164] Samadzadegan F, Toosi A, Dadrass Javan F. A critical review on multi-sensor and multi-platform remote sensing data fusion approaches: current status and prospects. International Journal of Remote Sensing, 2025; 46(3): 1327–1402.
[165] Kumar P, Pal K, Govil M C. Prioritized real-time multi-objective coverage path planning scheme for energy-constrained multi-UAVs. Sādhanā, 2025; 50(3): 1–19.
[166] Imran, Li J. Environmental and economic impact of UAV technology in agriculture. UAV aerodynamics and crop interaction: Revolutionizing modern agriculture with drone. Springer, 2025; pp.389–429. DOI: 10.1007/978-981-96-8402-1_12.
[167] Chen X. The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. Frontiers in Plant Science, 2025; 16: 1675657.
[168] Glen III C. Advancing agricultural biosecurity: Education and spatial solutions for small-scale farm resilience. Purdue University Graduate School, 2024. DOI: 10.25394/PGS.25675917.
[169] Holterman H J, Ter Horst M, Adriaanse P. Improving environmental risk assessment of pesticides: the need for advanced spray drift models in EU regulatory framework exploring modelling approaches for spray drift deposition for downward spraying for use in off-crop exposure assessment. EFSA Supporting Publications, 2025; 22(7): 9506E.
[170] ISO. Agricultural and forestry machinery — Unmanned aerial spraying systems — Part 1: Environmental requirements. Geneva, Switzerland; 2023.
[171] FAA. Large payload exempt aircraft list: United States Department of Transportation, 2024. https://www.faa.gov/uas/commercial_operators/part_107_waivers.
[172] Janke C, de Haag., Pik E, editors. Development of global regulations for uncrewed aircraft systems-Europe and beyond: a continued survey and evaluation of progress. 2025 Integrated Communications, Navigation and Surveillance Conference (ICNS), IEEE, 2025. DOI: 10.1109/ICNS65417.2025.10976863.
[173] ANAC. Regulations for remotely piloted aircraft systems (RPAS). 2023.
[174] Yamashita R, Kidoguchi K, Oshima T, Ishigaki A. Sustainable paddy farming in rural Japan: Leveraging farmer integration and agricultural UAVs for synergistic solutions. Journal of Cleaner Production, 2024; 475: 143685.
[175] Hewitt A J, Galea V J, O'Donnell C. Application technology for bioherbicides: challenges and opportunities with dry inoculum and liquid spray formulations. Pest Management Science, 2024; 80(1): 72–80.
[176] Raj M, Harshini N, Gupta S, Atiquzzaman M, Rawlley O, Goel L. Leveraging precision agriculture techniques using UAVs and emerging disruptive technologies. Energy Nexus, 2024; 14: 100300.
[177] Manu A, Osei J D, Lawler T. UAV-based remote sensing and artificial intelligence for climate-smart agriculture: A systematic review of technologies, analytics, and applications in smallholder systems. Preprints, 2026. DOI: 10.20944/preprints202603.0355.v1.
[178] Rahmati M. Edge AI-powered real-time decision-making for autonomous vehicles in adverse weather conditions. arXiv preprint arXiv: 250309638, 2025. DOI: 10.48550/arXiv.2503.09638.
[179] Saki M, Keshavarz R, Franklin D, Abolhasan M, Lipman J, Shariati N. A data-driven review of remote sensing-based data fusion in precision agriculture from foundational to transformer-based techniques. IEEE Access, 2025. DOI: 10.1109/ACCESS.2025.3610649.
[180] Alqudsi Y, Makaraci M. UAV swarms: research, challenges, and future directions. Journal of Engineering and Applied Science, 2025; 72(1): 12.