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ARTIFICIAL INTELLIGENCE-ENABLED UAVS FOR PRECISION CROP PROTECTION: APPLICATIONS IN PEST, DISEASE AND WEED MANAGEMENT

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ABSTRACT

The integration of artificial intelligence (AI) with unmanned aerial vehicles (UAVs) is emerging as an important approach for precision crop protection. UAV platforms equipped with RGB, multispectral, hyperspectral, thermal and LiDAR sensors can provide high-resolution information on crop condition, pest infestation, disease development and weed distribution. AI and machine-learning techniques enable automated interpretation of these data, facilitating crop-stress assessment, pest and disease detection, weed mapping and spatial decision-making. The integration of AI-based detection with GPS-guided and precision spraying systems further enables site-specific crop protection and potentially reduces unnecessary pesticide application. Recent developments in Internet of Things (IoT) connectivity, edge computing and autonomous navigation are extending UAV applications towards real-time monitoring and automated intervention. However, field-scale adoption remains constrained by battery endurance, payload limitations, spray drift, sensor and environmental variability, availability of representative training datasets, model generalization, computational requirements, cost and regulatory considerations. This review summarizes the major UAV platforms and sensing technologies used in precision crop protection, discusses AI-based approaches for pest, disease and weed detection, and examines their integration with targeted and variable-rate spraying. The role of IoT, edge computing and autonomous decision-making is also discussed, together with major technical and operational challenges. Overall, AI-enabled UAVs provide considerable potential for transforming conventional crop protection into a more precise, efficient, data-driven and sustainable management system.

Key words: Artificial intelligence; unmanned aerial vehicles; precision agriculture; pest management; machine learning; remote sensing

Introduction

Agriculture is undergoing a major technological transition driven by the need to increase productivity, improve resource-use efficiency and strengthen the sustainability of crop production systems. Conventional agricultural practices often rely on uniform application of fertilizers, irrigation and pesticides despite considerable spatial and temporal variability within fields. Such practices can increase input costs and result in unnecessary environmental exposure. Precision agriculture has therefore emerged as an alternative approach that integrates sensing technologies, remote sensing, geographical information systems, automation and data-driven decision-making to enable site-specific crop management. The development of digital agriculture has further expanded these possibilities through the integration of artificial intelligence (AI), machine learning, Internet of Things (IoT) devices, robotics and unmanned aerial vehicles (UAVs) (Kim *et al*., 2019; Subeesh and Mehta, 2021).

Among these technologies, UAVs, commonly referred to as drones, have attracted considerable attention because of their ability to acquire high-resolution information rapidly over agricultural fields. Unlike satellite-based remote sensing, UAVs can operate at relatively low altitudes and can be deployed according to crop-specific requirements, allowing flexible acquisition of spatially detailed information. Multirotor UAVs are particularly suitable for agricultural applications because their hovering capability, manoeuvrability and low-altitude operation facilitate detailed observation of crop canopies and field variability (Kim *et al*., 2019; Tsouros *et al*., 2019; Velusamy *et al*., 2021). UAV platforms can accommodate RGB, multispectral, hyperspectral and thermal sensors, providing information on crop vigour, physiological status, water stress and other changes that may not be readily identified through conventional field scouting (Barbedo, 2019; Zhang and Zhu, 2023).

The application of UAV-based remote sensing has become increasingly important for crop-health monitoring and the detection of pests and diseases. High-resolution aerial imagery can reveal spatial patterns associated with crop stress and disease development, while multispectral and hyperspectral imaging provides information beyond the visible spectrum. Thermal sensing can additionally reveal changes associated with plant water status and physiological stress. UAV-based imaging has consequently been investigated for disease assessment, disease-severity estimation and crop-health monitoring across several agricultural systems (Francesconi *et al*., 2021; Guo *et al*., 2021; Yu *et al*., 2021). Machine-learning approaches further enhance these capabilities by extracting relevant features from aerial images and classifying disease symptoms or pest-associated damage. Deep-learning models, particularly convolutional neural networks (CNNs), have demonstrated potential for automated pest and disease detection (Dey *et al*., 2022; Tetila *et al*., 2020).

The integration of AI with UAV technology has consequently shifted agricultural drones from simple image-acquisition platforms towards intelligent decision-support systems. AI algorithms can process large volumes of imagery and sensor data to identify crop variability, detect pest infestations, classify diseases, identify weeds and support crop-stress assessment. Computer-vision systems can analyse aerial images, while machine-learning algorithms can convert image-derived information into actionable management decisions (Jha *et al*., 2019; Subeesh and Mehta, 2021). UAV-based computer vision has also been investigated for identifying weed-infested areas and supporting site-specific herbicide management, demonstrating the potential of AI-assisted technologies to reduce unnecessary chemical application (Sapkota *et al*., 2023).

An important emerging application is the integration of UAV sensing with precision pesticide spraying. Conventional pesticide application may result in excessive chemical use and off-target losses when pest populations are unevenly distributed within fields. UAV-based spraying provides opportunities for controlled flight paths, adjustable spray parameters and localized treatment. The effectiveness of UAV spraying depends on factors such as droplet size, spray volume, nozzle configuration, flight altitude, flight speed and environmental conditions. Consequently, combining AI-based target identification with an appropriately calibrated spraying system can facilitate a transition from uniform application towards site-specific and potentially variable-rate crop protection.

The relevance of these technologies is particularly important in India, where diverse cropping systems, variable farm sizes, labour constraints and increasing requirements for efficient input management create a need for scalable precision-agriculture technologies. UAV adoption is expanding through technological development and increasing interest in precision crop management, although initial investment, limited flight endurance and payload capacity, technical expertise, regulatory requirements and inadequate supporting infrastructure remain important constraints (Puppala *et al*., 2023).

Thus, the convergence of UAVs, advanced sensors, AI, machine learning, IoT and precision spraying represents an important development in modern crop protection. These technologies have the potential to integrate crop surveillance, pest and disease detection, decision-making and targeted intervention within a single digital framework. However, successful field deployment requires reliable sensing, robust AI models, appropriate spray calibration, environmental consideration, economic feasibility and farmer accessibility. Therefore, this review examines the technological development and applications of AI-enabled UAVs in precision agriculture, with particular emphasis on crop-health monitoring, pest and disease detection, intelligent pesticide spraying, IoT and autonomous systems, operational challenges and future prospects for sustainable crop protection.

Drone Technology for Precision Crop Protection

Agricultural unmanned aerial vehicles (UAVs) are available in different configurations, principally fixed-wing, multirotor, single-rotor and hybrid vertical take-off and landing (VTOL) platforms. Fixed-wing UAVs are suitable for large-area mapping and crop surveillance because of

their greater flight endurance and coverage, although they have limited hovering and manoeuvrability. Multirotor UAVs, in contrast, can hover, take off and land vertically and operate at low altitude, making them particularly suitable for detailed crop inspection and precision spraying (Matese *et al*., 2015; Hunt and Daughtry, 2018).

The operational suitability of a UAV depends on its payload, endurance, propulsion system and mission requirements. Electric propulsion is commonly used because of its relatively simple operation and maintenance, whereas hybrid propulsion systems are being explored to extend flight duration (Townsend *et al*., 2020). UAV performance is also influenced by aircraft design, rotor configuration and flight-control systems (Laghari *et al*., 2023; Rinaldi *et al*., 2023).

For precision crop protection, UAVs can be configured for surveying, monitoring or spraying. Surveying platforms generally carry high-resolution cameras or LiDAR, monitoring UAVs are equipped with multispectral or thermal sensors, whereas spraying platforms incorporate tanks, pumps, flow-control units and nozzles for targeted delivery of crop-protection inputs (Radoglou-Grammatikis *et al*., 2020; Toscano *et al*., 2024).

Flight planning and navigation are important for achieving accurate field coverage. GPS/GNSS-based navigation permits predefined flight paths, while autonomous systems can combine positioning information with onboard sensors to perform repetitive missions with reduced operator intervention. Payload capacity and flight endurance remain important limitations because increased payload can reduce operating time and increase the number of sorties required for field treatment (Velusamy *et al*., 2021; Unde *et al*., 2025).

Recent UAV developments increasingly integrate advanced sensors, onboard computing, variable-rate application systems and autonomous control. These developments allow UAV platforms to combine aerial data acquisition with automated analysis and site-specific management, thereby providing an important technological foundation for AI-assisted crop monitoring and precision spraying (Unde *et al*., 2025).

Sensors and Imaging Technologies for Precision Crop Protection

The effectiveness of UAV-based crop protection depends substantially on the sensing system used to acquire information from the crop canopy. Different sensors capture complementary characteristics of vegetation, ranging from visible structural changes to physiological responses that may occur before symptoms become visually apparent. Consequently, sensor selection determines the type and quality of information available for subsequent crop-health assessment and automated decision-making (Lu *et al*., 2020; Toscano *et al*., 2024).

RGB cameras are among the most widely used and relatively inexpensive UAV sensors. They capture visible red, green and blue wavelengths and provide high-resolution images suitable for crop mapping, plant counting, canopy assessment and identification of visibly damaged or infested areas. Jin *et al*., (2017) demonstrated the potential of very-low-altitude UAV RGB imagery for estimating wheat plant density, showing a strong relationship between image-derived estimates and field measurements.

Multispectral sensors capture selected spectral regions, generally including visible and near-infrared wavelengths. Their ability to quantify differences in vegetation reflectance enables calculation of indices such as NDVI and assessment of crop vigour, chlorophyll status and physiological stress. UAV-based multispectral imagery has also been applied to estimate crop yield and nitrogen-use efficiency (Liu *et al*., 2022).

Hyperspectral imaging provides considerably greater spectral detail by recording numerous narrow, contiguous wavelength bands. This allows subtle biochemical and physiological changes associated with disease, nutrient deficiency and pest stress to be investigated. Lu *et al*., (2020) highlighted the expanding application of hyperspectral imaging for agricultural assessment, while Guo *et al*., (2021) demonstrated the potential of UAV-based hyperspectral imagery for detecting wheat yellow rust.

Thermal sensors measure canopy temperature and can reveal plant water stress and other physiological disturbances. Their value is particularly important where stress produces temperature changes before obvious visual symptoms develop. UAV-based thermal and RGB imaging has also been investigated for detecting Fusarium head blight in durum wheat (Francesconi *et al*., 2021).

LiDAR provides three-dimensional information by measuring the return of laser pulses from vegetation and ground surfaces. It can therefore characterize canopy structure, plant height and biomass and complement spectral information obtained from optical sensors. Maimaitijiang *et al*., (2020) compared UAV-based LiDAR and photogrammetric approaches for monitoring sorghum growth.

The increasing availability of multi-sensor UAV platforms is particularly important for precision crop protection because structural, spectral and thermal

information can be combined to improve the characterization of crop condition and stress. Multi-sensor integration therefore provides an important foundation for machine-learning and AI-based analysis, enabling UAV imagery to be converted into crop-health information, pest or disease distribution maps and management decisions (Pádua *et al.*, 2020; Toscano *et al.*, 2024).

Artificial Intelligence in UAV-Based Crop Monitoring and Pest Management

Artificial intelligence (AI) has strengthened the application of UAVs in precision agriculture by enabling automated interpretation of aerial imagery for crop-health assessment, pest detection and management decisions. Machine learning (ML), deep learning (DL) and computer vision can process RGB, multispectral and hyperspectral imagery and identify patterns associated with crop stress, pest infestation and disease development (Jha *et al.*, 2019). ML algorithms, including Random Forest, support vector machines and decision-tree approaches, can combine spectral and spatial characteristics to classify crop conditions and support site-specific management.

Deep-learning approaches, particularly convolutional neural networks (CNNs), have improved automated image analysis because they can extract relevant spatial features with limited dependence on manually defined characteristics. UAV-based multispectral imagery combined with deep-learning segmentation has been successfully applied for disease identification in vineyards (Kerkech *et al.*, 2020). Similarly, UAV RGB imagery has enabled autonomous identification of *Spodoptera frugiperda* based on characteristic feeding symptoms, demonstrating the potential of aerial platforms for pest detection through crop damage signatures (Feng *et al.*, 2022).

AI-based computer vision can perform classification, object detection and image segmentation, providing progressively greater spatial information for crop-protection applications. Classification assigns images or image regions to predefined categories, object-detection models identify and localize specific targets, while segmentation delineates affected areas at the pixel or region level. Reliable model development requires representative field observations and appropriate reference measurements for validation, particularly when models are intended for field-scale deployment (Kaivosoja *et al.*, 2021).

The integration of AI with UAVs is increasingly moving towards real-time operation. Geetha and Deepika (2024) combined RGB and multispectral imagery with a deep-learning-based pest-detection system and linked detected pest locations with GPS-guided localized spraying. Their system reported a mean average precision (mAP) of 94.8 and a 31% reduction in pesticide use compared with conventional spraying, demonstrating the potential of integrating detection and intervention within a single precision-agriculture framework.

Further improvement can be achieved by combining UAV imagery with environmental information from IoT sensors. Soil moisture, temperature and humidity measurements can provide additional environmental context for interpreting crop condition and pest occurrence. However, variations in illumination, crop growth stage, pest density, canopy structure and field conditions can affect AI model performance and generalization. Therefore, larger and more diverse datasets, rigorous field validation and efficient computational systems are required for reliable field-scale deployment.

AI-Enabled Precision Spraying and Targeted Crop Protection

The integration of artificial intelligence (AI) with UAV-based spraying is enabling a shift from uniform pesticide application towards site-specific crop protection. In conventional spraying, treatment may be applied across the entire crop area even when pest or disease incidence is spatially variable. AI-enabled systems can instead identify affected locations from aerial imagery, determine treatment requirements and guide spraying towards designated coordinates. This integration connects crop monitoring with automated intervention and provides a basis for improving pesticide-use efficiency (Filho *et al.*, 2020; Anam *et al.*, 2024).

AI-enabled precision spraying generally involves image acquisition, target detection, decision-making, spray activation and application monitoring. UAVs equipped with RGB, multispectral or other sensors acquire crop images, which are processed using computer-vision and deep-learning algorithms. Detected targets can then be associated with geographic coordinates, allowing electronically controlled spraying systems to activate at the required locations. Depending on system design, treatment may be based on previously generated prescription maps or performed during real-time UAV operation (Zanin *et al.*, 2022).

The physical spraying system remains critical for achieving biological efficacy. Spray volume, nozzle configuration, droplet characteristics, flight altitude and flight speed influence deposition and pest-control performance. Field evaluation in wheat demonstrated that

UAV spray volume and nozzle size significantly affected deposition and control efficacy against wheat aphid and powdery mildew (Wang *et al*., 2019). UAV-assisted pesticide application has also demonstrated potential for pest and disease management in rice (Ragiman *et al*., 2024). In orchard systems, additional challenges arise because rotor-generated airflow interacts with complex canopy architecture and influences spray deposition and penetration.

Targeted spraying has also been evaluated against citrus pests, including *Diaphorina citri*, demonstrating the applicability of UAV-based insecticide application to perennial crops (Miranda *et al*., 2023). Comparative evaluation of knapsack, boom and drone sprayers has similarly demonstrated differences in spray performance and weed-control efficiency in soybean (Hiremath *et al*., 2024). The integration of AI with adaptive spraying can further enable variable-rate application, whereby spray intensity is adjusted according to pest density or the severity of the detected target.

Applications of AI-Enabled UAVs in Pest, Disease and Weed Management

AI-enabled UAVs are increasingly being applied across major components of crop protection, particularly insect pest detection, plant disease surveillance and weed mapping. Their principal advantage is the ability to combine high-resolution aerial observations with automated image interpretation, thereby generating spatial information for timely and localized management. The application of these technologies varies according to the biological target and the visual or spectral characteristics produced by crop stress or damage.

Insect pest management

UAV-based pest management can involve direct detection of insects as well as identification of characteristic feeding damage. UAV RGB imagery has been successfully used to identify *Spodoptera frugiperda* based on characteristic feeding symptoms, providing an alternative approach where individual insects are difficult to detect from aerial platforms (Feng *et al*., 2022). Deep-learning-based UAV imagery has also demonstrated potential for automated detection of insect pests in soybean, highlighting the applicability of computer vision to pest surveillance (Tetila *et al*., 2020). Such approaches can facilitate pest hotspot mapping and support targeted intervention rather than uniform treatment.

Disease detection and management

Disease assessment is another important application because infection can alter plant spectral characteristics, canopy temperature and structural properties. UAV-based remote sensing has been used for the detection and spatial assessment of several crop diseases. Hyperspectral UAV imagery, for example, has demonstrated potential for detecting wheat yellow rust, while thermal and RGB observations have been investigated for Fusarium head blight assessment (Guo *et al*., 2021; Francesconi *et al*., 2021). These approaches can facilitate early identification of disease patches and repeated monitoring of disease development, thereby supporting localized crop-protection interventions.

Weed management

Weed detection is particularly suited to UAV-based precision management because weeds frequently occur in spatially heterogeneous patches. RGB and multispectral imagery can differentiate crops from weeds based on morphological and spectral characteristics, while AI algorithms can generate weed-distribution maps for site-specific herbicide application. Low-cost UAV platforms combined with open-source GIS have demonstrated potential for semi-automatic weed mapping (Mattivi *et al*., 2021). Similarly, UAS imagery and computer-vision approaches have been investigated for reducing chemical inputs through site-specific weed management (Sapkota *et al*., 2023).

Overall, AI-enabled UAVs can support detection, spatial mapping, monitoring and targeted intervention across diverse crop-protection problems. Their effectiveness will depend on robust datasets, multi-season validation and integration of detection systems with reliable field-level control technologies.

Integration of UAVs with IoT, Edge Computing and Autonomous Decision-Making

The integration of UAVs with the Internet of Things (IoT) can extend precision crop protection from aerial monitoring towards data-driven decision-making. UAV imagery provides spatial information on crop condition and pest distribution, whereas ground-based sensors can provide environmental variables such as temperature, relative humidity and soil moisture. The combination of aerial and ground-based observations can provide additional environmental context for interpreting crop and pest conditions (Khan *et al*., 2023).

IoT-enabled systems can facilitate communication between UAVs, field sensors and farm-management platforms. Environmental observations can be integrated with UAV-derived information and historical records to support identification of conditions favourable for pest development and improve the timing of field scouting or intervention. Recent AI-driven UAV frameworks have

demonstrated the feasibility of integrating RGB and multispectral imagery with soil moisture, temperature and humidity measurements for precision pest management (Geetha and Deepika, 2024).

A major limitation of cloud-dependent systems is the delay associated with transferring large volumes of UAV imagery for remote processing. Edge computing addresses this limitation by processing data closer to the point of acquisition. AI models deployed on edge devices can potentially analyse imagery and generate decisions with reduced communication requirements. Edge-based crop-disease monitoring has been proposed to reduce processing latency, although limited computational resources and model generalization remain important challenges (Huang *et al*., 2023).

Autonomous decision-making represents the next step in UAV-based crop protection, linking sensing and AI-based interpretation with automated intervention. GPS/GNSS positioning, flight-control systems and precision spraying units can allow UAVs to respond to identified crop-protection targets. Integrated systems have demonstrated the feasibility of connecting UAV image acquisition, IoT monitoring, AI-based pest detection and GPS-controlled localized spraying within a common operational framework.

The integration of UAV sensing, IoT monitoring, edge AI and autonomous control therefore provides a pathway towards closed-loop crop protection in which field conditions are sensed, analysed and acted upon with reduced human intervention. However, stable communication, adequate computing capacity, battery endurance, positioning accuracy and robust algorithms remain necessary for reliable field-scale deployment.

Challenges and Limitations of AI-Enabled UAVs in Crop Protection

Despite their potential for improving precision crop protection, AI-enabled UAV systems face several technical, economic, environmental and operational constraints. One of the major limitations is battery endurance. Multirotor UAVs carrying imaging or spraying payloads generally have limited flight duration, requiring frequent battery replacement or recharging and increasing the number of sorties required for large fields. Payload weight further affects endurance and operational efficiency (Townsend *et al*., 2020).

The quality and availability of training datasets represent another important limitation for AI-based crop-protection systems. Pest and disease images can vary substantially with crop species, growth stage, illumination, background vegetation, pest density and environmental conditions. Models trained using restricted datasets may therefore show reduced accuracy when applied to different crops or geographical regions. Development of diverse, well-annotated and multi-season datasets is essential for improving model robustness, transferability and reliability under field conditions (Barbedo, 2019).

Small insect pests present an additional challenge because their size relative to UAV imagery can be extremely small (Kaivosoja *et al*., 2021). Occlusion by leaves, similarity between pest damage and abiotic stress, variable illumination and complex crop canopies can further complicate automated detection. Deep-learning-based pest detection has demonstrated considerable potential, but reliable recognition under variable field conditions remains challenging, particularly when target objects occupy only a small proportion of the image (Tetila *et al*., 2020).

For spraying operations, weather conditions and spray drift can substantially influence application accuracy. Wind speed, temperature and relative humidity affect droplet movement, evaporation and deposition. Dense crop canopies may also restrict penetration and produce uneven deposition, particularly on lower and inner leaf surfaces. Consequently, AI-based target identification must be complemented by appropriate nozzle selection, flight parameters and spray calibration. UAV spraying studies have demonstrated that application parameters such as spray volume and nozzle characteristics can significantly influence deposition and pest-control efficacy (Wang *et al*., 2019).

Economic considerations remain important, particularly for small and fragmented farms. Initial expenditure on UAV platforms, sensors, batteries, AI infrastructure and maintenance can be substantial. In addition, operators require training in UAV operation, image processing, AI systems and pesticide application. Limited technical expertise, infrastructure requirements and regulatory constraints can further influence adoption, particularly in developing agricultural systems (Puppala *et al*., 2023).

Therefore, wider adoption requires cost-effective platforms, robust AI models, standardized operating protocols, improved battery technology, reliable communication and appropriate regulatory frameworks. Addressing these limitations will be essential for translating experimental UAV applications into dependable field-scale crop-protection systems.

Conclusion

AI-enabled UAVs offer considerable potential for precision crop protection by integrating aerial sensing,

automated pest and disease detection and targeted intervention. The combination of advanced sensors, AI-based image analysis and precision spraying can improve input-use efficiency and reduce unnecessary pesticide application. However, limitations related to battery endurance, spray drift, AI model generalization, cost, regulation and field validation remain important barriers to large-scale adoption. Future research should focus on robust multi-season AI models, real-time edge processing, improved spraying technologies and integration with integrated pest management strategies. Overall, AI-enabled UAVs can support a transition towards more precise, efficient and sustainable crop-protection systems.

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References

Anam, I., Arafat N., Hafiz M.S., Jim J.R., Kabir M.M. and Mridha M.F. (2024). A systematic review of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture. *Smart Agricultural Technology*, **9**, 100647. https://doi.org/10.1016/j.atech.2024.100647.

Barbedo, J.G.A. (2019). A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. *Drones*, **3**, 40. https://doi.org/10.3390/drones3020040.

Dey, B., MasumUlHaque M., Khatun R. and Ahmed R. (2022). Comparative performance of four CNN-based deep learning variants in detecting Hispa pest, two fungal diseases, and NPK deficiency symptoms of rice (*Oryza sativa*). *Computers and Electronics in Agriculture*, **202**, 107340. https://doi.org/10.1016/j.compag.2022.107340.

Feng, J., Sun Y., Zhang K., Zhao Y., Ren Y. and Chen Y., *et al*. (2022). Autonomous detection of *Spodoptera frugiperda* by feeding symptoms directly from UAV RGB imagery. *Applied Sciences*, **12**, 2592.

Filho, F.H.I., Heldens W.B., Kong Z. and De Lange E.S. (2020). Drones: Innovative technology for use in precision pest management. *Journal of Economic Entomology*, **113**, 1-25.

Francesconi, S., Harfouche A., Maesano M. and Balestra G.M. (2021). UAV-based thermal, RGB imaging and gene expression analysis allowed detection of *Fusarium* head blight and gave new insights into the physiological responses to the disease in durum wheat. *Frontiers in Plant Science*, **12**, 628575. https://doi.org/10.3389/fpls.2021.628575.

Geetha, K. and Deepika J. (2024). AI-driven drone-assisted smart farming framework for precision pest control and crop yield optimization. *National Journal of Smart Agriculture and Rural Innovation*, **2(2)**, 11–19.

Guo, A. *et al*. (2021). Wheat yellow rust detection using UAV-based hyperspectral technology. *Remote Sensing*, **13(1)**, 123. https://doi.org/10.3390/rs13010123.

Huang, L., Chen X. and Li J. (2023). Edge AI-powered crop disease monitoring using UAV imaging. *IEEE Transactions on Automation Science and Engineering*, **20(3)**, 1341–1353.

Hiremath, C., Khatri N. and Jagtap M.P. (2024). Comparative studies of knapsack, boom, and drone sprayers for weed management in soybean (*Glycine max* L.). *Environmental Research*, **240**, 117480. https://doi.org/10.1016/j.envres.2023.117480.

Hunt, E.R. Jr. and Daughtry C.S.T. (2018). What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *International Journal of Remote Sensing*, **39**, 5345–5376. https://doi.org/10.1080/01431161.2017.1410300.

Jha, K., Doshi A., Patel P. and Shah M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, **2**, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004.

Jiang, J. *et al*. (2026). UAV-based spraying in orchard systems: Mechanisms, performance indicators, and integrated applications. *Pest Management Science*, **82(6)**, 5107–5125.

Jin, X., Liu S., Baret F., Hemerlé M. and Comar A. (2017). Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. *Remote Sensing of Environment*, **198**, 105–114. https://doi.org/10.1016/j.rse.2017.06.007.

Kaivosoja, J., Hautsalo J., Heikkinen J., Hiltunen L., Ruuttunen P. and Näsi R. *et al*. (2021). Reference measurements in developing UAV systems for detecting pests, weeds, and diseases. *Remote Sensing*, **13**, 1238.

Kerkech, M., Hafiane A. and Canals R. (2020). Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach. *Computers and Electronics in Agriculture*, **174**, 105446. https://doi.org/10.1016/j.compag.2020.105446.

Khan, R., Singh P. and Kumar J. (2023). IoT-based monitoring and decision-making framework for smart farming. *Sensors*, **23(5)**, 2345–2358. https://doi.org/10.3390/s23052345.

Kim, J., Kim S., Ju C. and Son H.I. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access*, **7**, 105100–105115.

Laghari, A.A., Jumani A.K., Laghari R.A. and Nawaz H. (2023). Unmanned aerial vehicles: A review. *Cognitive Robotics*, **3**, 8–22. https://doi.org/10.1016/j.cogr.2022.12.004.

Liu, J., Zhu Y., Tao X., Chen X. and Li X. (2022). Rapid

prediction of winter wheat yield and nitrogen use efficiency using consumer-grade unmanned aerial vehicles multispectral imagery. *Frontiers in Plant Science*, **13**, 1032170. https://doi.org/10.3389/fpls.2022.1032170.

Lu, B., Dao P.D., Liu J., He Y. and Shang J. (2020). Recent advances of hyperspectral imaging technology and applications in agriculture. *Remote Sensing*, **12**, 2659. https://doi.org/10.3390/rs12162659.

Maimaitijiang, M., Sagan V., Erkbol H., Adrian J., Newcomb M., LeBauer D., Pauli D., Shakoor N. and Mockler T.C. (2020). UAV-based sorghum growth monitoring: A comparative analysis of LiDAR and photogrammetry. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, **3**, 489–496. https://doi.org/10.5194/isprs-annals-V-3-2020-489-2020.

Matese, A., Toscano P., Di Gennaro S.F., Genesio L., Vaccari F.P., Primicerio J., Belli C., Zaldei A., Bianconi R. and Gioli B. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sensing*, **7(3)**, 2971–2990. https://doi.org/10.3390/rs70302971

Mattivi, P., Pappalardo S.E., Nikolic N., Mandolesi L., Persichetti A., De Marchi M. and Masin R. (2021). Can commercial low-cost drones and open-source GIS technologies be suitable for semi-automatic weed mapping for smart farming? A case study in NE Italy. *Remote Sensing*, **13**, 1869. https://doi.org/10.3390/rs13101869.

Miranda, M.P., Eduardo W.I., Scapin M.S., Volpe H.X.L., Rodriguez G.M., Vizoni M.C. and Hakvoort R.B.J. (2023). Insecticide application using an unmanned aerial vehicle for *Diaphorina citri* control in citrus orchards. *Journal of Applied Entomology*, **147(9)**, 716–727.

Pádua, L., Adão T., Sousa A., Peres E. and Sousa J.J. (2020). Individual grapevine analysis in a multi-temporal context using UAV-based multi-sensor imagery. *Remote Sensing*, **12(1)**, 139. https://doi.org/10.3390/rs12010139

Puppala, H., Peddinti P.R., Tamvada J.P., Ahuja J. and Kim B. (2023). Barriers to the adoption of new technologies in rural areas: The case of unmanned aerial vehicles for precision agriculture in India. *Technology in Society*, **74**, 102335. https://doi.org/10.1016/j.techsoc.2023.102335.

Radoglou-Grammatikis, P., Sarigiannidis P., Lagkas T. and Moscholios I. (2020). A compilation of UAV applications for precision agriculture. *Computer Networks*, **172**, 107148. https://doi.org/10.1016/j.comnet.2020.107148.

Ragiman, S., Talluri K.B. and NRG V. *et al.* (2024). Unmanned aerial vehicle (UAV)-assisted pesticide application for pest and disease prevention and control in rice. *International Journal of Agricultural and Biological Engineering*, **17(5)**, 88–95.

Rinaldi, M., Primatesta S. and Guglieri G. (2023). A comparative study for control of quadrotor UAVs. *Applied Sciences*, **13(6)**, 3464. https://doi.org/10.3390/app13063464.

Sapkota, R., Stenger J., Ostlie M. and Flores P. (2023). Towards reducing chemical usage for weed control in agriculture using UAS imagery analysis and computer vision techniques. *Scientific Reports*, **13**, 6548. https://doi.org/10.1038/s41598-023-33042-0.

Shahi, T.B., Xu C.Y., Neupane A. and Guo W. (2023). Recent advances in crop disease detection using UAV and deep learning techniques. *Remote Sensing*, **15(9)**, 2450. https://doi.org/10.3390/rs15092450.

Subeesh, A. and Mehta C.R. (2021). Automation and digitization of agriculture using artificial intelligence and internet of things. *Artificial Intelligence in Agriculture*, **5**, 278–291. https://doi.org/10.1016/j.aiia.2021.11.004.

Tetila, E.C., Machado B.B., Astolfi G., Belete N.A.S., Amorim W.P., Roel A.R. and Pistori H. (2020). Detection of soybean pests using deep learning and UAV images. *Computers and Electronics in Agriculture*, **179**, 105836. https://doi.org/10.1016/j.compag.2020.105836

Townsend, A., Jiya I.N., Martinson C., Bessarabov D. and Gouws R. (2020). A comprehensive review of energy sources for unmanned aerial vehicles, their shortfalls and opportunities for improvements. *Heliyon*, **6**, e05285.

Toscano, F., Fiorentino C., Capece N., Erra U., Travascia D., Scopa A., Drosos M. and D'Antonio P. (2024). Unmanned aerial vehicle for precision agriculture: A review. *IEEE Access*, **12**, 69188–69205.

Tsouros, D.C., Bibi S. and Sarigiannidis P.G. (2019). A review on UAV-based applications for precision agriculture. *Information*, **10(11)**, 349. https://doi.org/10.3390/info10110349.

Unde, S.S., Kurkute V.K., Chavan S.S., Mohite D.D., Harale A.A. and Chougle A. (2025). [UAV/AI-based precision-agriculture review]. *Discover Mechanical Engineering*, **4**, 38.

Velusamy, P., Rajendran S., Mahendran R.K., Naseer S., Shafiq M. and Choi J.G. (2021). Unmanned aerial vehicles (UAV) in precision agriculture: Applications and challenges. *Energies*, **15(1)**, 217. https://doi.org/10.3390/en15010217.

Wang, G., Lan Y., Qi H., Chen P., Hewitt A. and Han Y. (2019). Field evaluation of an unmanned aerial vehicle (UAV) sprayer: Effect of spray volume on deposition and the control of pests and disease in wheat. *Pest Management Science*, **75**, 1546–1555.

Yu, R., Luo Y., Zhou Q., Zhang X., Wu D. and Ren L. (2021). Early detection of pine wilt disease using deep learning algorithms and UAV-based multispectral imagery. *Forest Ecology and Management*, **497**, 119493.

Zanin, A.R.A., Neves D.C., Teodoro L.P.R., da Silva Júnior C.A., da Silva S.P. and Teodoro P.E. *et al.* (2022). Reduction of pesticide application via real-time precision spraying. *Scientific Reports*, **12**, 5638.

Zhang, Z. and Zhu L. (2023). A review on unmanned aerial vehicle remote sensing: Platforms, sensors, data processing methods, and applications. *Drones*, **7(6)**, 398. https://doi.org/10.3390/drones7060398.