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SMART DETECTION OF CROP DISEASES: UAV APPLICATIONS IN THE ERA OF PRECISION PLANT PATHOLOGY

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ABSTRACT

Against the backdrop of global food security concerns and the impending threat of phytopathogens, precision plant pathology technology has emerged as a key tool in ensuring the optimisation of agricultural sustainability. The conventional methods adopted in crop disease diagnosis, based on visual examination and laboratory analysis, are found to be lacking in terms of providing timely, geographically precise and scalable solutions. With recent advances in Unmanned Aerial Vehicle (UAV), or drone, technology, there is a paradigm shift in meeting such challenges. This review discusses in depth the synergistic integration of UAVs with multispectral, hyperspectral, thermal, and RGB imaging modalities in conjunction with artificial intelligence (AI) and deep learning approaches for the detection, classification, and quantification of diseases in plants at an early stage. Machine learning algorithms and optical sensors on unmanned aerial vehicles (UAVs) enable real-time high-resolution monitoring of disease signs on large crop fields. Vegetation indices, thermal stress maps, and spectral signatures are used by these systems to detect subtle physiological changes in crops before any visible sign of the disease. Their uses include disease detection, irrigation optimization, nutrient mapping, aerial sowing, yield prediction and precision pesticide application. Deep learning models, particularly CNNs and U-Net architectures, show the high accuracy of disease diagnosis and the estimation of their severity in field scenarios. In addition, UAV-based systems are fully compatible with Geographic Information Systems (GIS), IoTs, and cloud platforms, which facilitate data-driven decision-making for crop management. Nevertheless, there are obstacles in the shape of high data acquisition costs, model generalizability, regulatory restrictions, and low dataset diversity. The current article is concerned with recent developments, field-scale case studies, and existing challenges and discusses future directions for drone-based plant disease monitoring. The integration of UAV technologies with AI is highly promising to change the face of plant pathology and render disease monitoring more accurate, proactive, and sustainable.

Key words : Unmanned Aerial Vehicles (UAVs), Precision Plant Pathology, Plant Disease Detection, Artificial Intelligence (AI) in Agriculture, Smart Farming, Drone-based Crop Monitoring.

Introduction

Global agricultural food production must rise by a minimum of 70% to satisfy the demands of the growing world population (Ahirwar *et al*, 2019). In recent years, the incidence of disorders attributable to bacterial, fungal, and viral infections has risen. Infections impact plants at many phases of agricultural development. Contingent upon meteorological circumstances and the phytosanitary status of crops, disease prevalence may attain 70–80% of the total plant population, with production reductions potentially plummeting to 80–98% in certain instances. Plants possess inherent cellular immunity; yet, certain phytopathogens can circumvent this defence (Nazarov *et al*, 2020). Losses may reach as high as 30% during storage, transit and distribution to the customer (Gustafsson *et al*, 2013). Consequently, it is imperative to apprehend or inhibit the emergence of infectious illnesses throughout all phases of crop production, commencing with seed handling techniques and concluding with delivery.

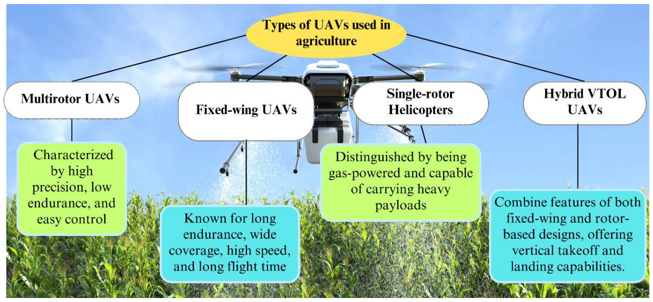
In the present age marked by substantial technical progress, it is remarkable that farmers persist in using conventional methods for disease diagnosis in crops. Farmers continue to manually and visually inspect crops for symptoms of illness instead of relying on contemporary specialised instruments (Shaikh *et al*, 2022). Conventional techniques of visually assessing and appraising crops completely reliant on the farmer's competence provide several obstacles and constraints in agricultural research. In a worst-case situation, an undiscovered crop infection might lead to a complete decrease in the crop, adversely affecting production. Some agricultural illnesses may display subtle signs, complicating the identification of the proper course of treatment. In such circumstances, it might be perplexing to choose the most effective judgement, nature and intervention strategy. Consequently, it is imperative to do a sophisticated and thorough study (Munjal *et al*, 2023). Conventional, genetic, and serological techniques often employed for plant disease detection frequently prove ineffectual if not utilised during the early phases of pathogenesis, when symptoms are absent or minimal. Furthermore, they are nearly ineffective in obtaining spatially resolved diagnostic outcomes for plant diseases (Abbas *et al*, 2023).

Conversely, remote sensing (RS) methodologies employing drones are highly efficient for the swift detection of plant diseases in their first phases. Drones now serve a crucial role in monitoring the spread, identification and diagnosis of plant pathogens to maintain crop health. The benefits of drone technology encompass elevated spatial resolution due to several onboard sensors, enhanced efficiency, operational versatility, and notably, rapid identification of plant diseases across extensive areas at little expense, with dependability and availability of high-resolution data. Drone technology utilises an automated process that starts with the acquisition of photos of infected plants using diverse sensors and cameras. After feature extraction, image processing methodologies employ suitable classical machine learning or deep learning techniques. Features are derived from leaf pictures with edge detection and histogram equalisation techniques. Drones have several potential applications in agriculture, such as minimising physical effort and enhancing output. Drones might offer early detection of plant diseases, enabling farmers to avert expensive crop failures (Abbas *et al*, 2023).

The utilisation of drones for crop monitoring and pesticide application in Precision Agriculture (PA). The tasks undertaken pertain to drone architecture, the advancement of numerous sensor technologies, and innovations in localised spraying techniques. Furthermore, the application of Artificial Intelligence (AI) and deep learning for the remote surveillance of crops has been examined (Hafeez *et al*, 2023). A multitude of drone applications has been devised for various purposes, including pest detection, crop yield prediction, crop spraying, yield estimation, water stress detection, land mapping, identification of nutrient deficiencies in plants, weed detection, livestock management, protection of agricultural products, and soil analysis (Celen *et al*, 2020). This paper seeks to examine the function of unmanned aerial vehicles (UAVs) in the intelligent identification of agricultural diseases within the context of precision plant pathology. It emphasises the amalgamation of UAV-based imaging technologies with artificial intelligence for prompt, precise, and non-invasive illness detection. The evaluation encompasses many sensor categories, data analytical techniques, and applications tailored to certain crops. Furthermore, it underscores existing limits, practical case studies, and prospective avenues in UAV-assisted plant disease control.

UAV Technology: Components and Capabilities

Types of UAVs used in agriculture

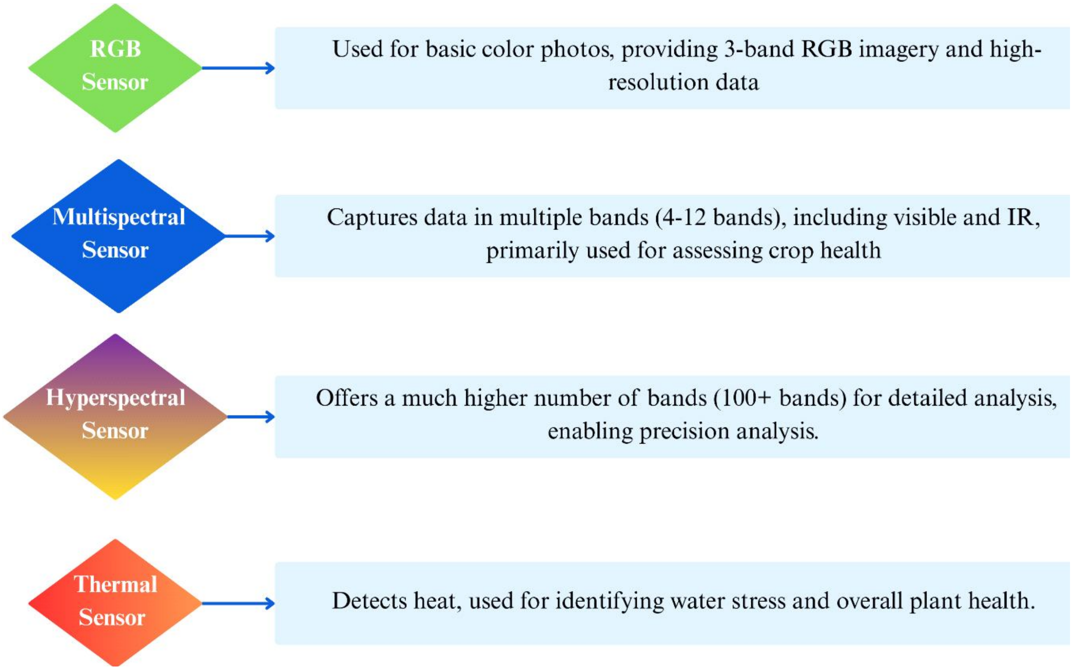


Flowchart 1 : Different types of UAVs used in Agriculture.

Unmanned Aerial Vehicles (UAVs) come in various configurations, each tailored to specific agricultural needs such as disease surveillance, spraying, and mapping. Their structural design—ranging from multi-rotor to fixed-wing and hybrid VTOL models—determines their flight capability, coverage area, and operational efficiency in precision farming. Multi-rotor drones represent the most straightforward category, providing enhanced precision at the expense of endurance and velocity. Fixed-wing rotor drones utilise wing-like structures and need external force for take-off. Single-rotor helicopter drones have more benefits owing to their gas-controlled systems and elongated rotor blades, rendering them more effective in agricultural applications. Fixed-wing hybrid VTOL (Vertical Take-off and Landing) drones integrate UAV characteristics with the capability to hover in a stationary position, hence preserving their hybrid attributes. These drones may ascend from a single location and maintain a vertical position over a designated region. A single eBee flight captures data on the Vegetation Index, CCCI, NDRE, MCARI, CWSI, plant counts, soil moisture levels, soil temperature, and 3D mapping/topography (Dileep *et al*, 2020).

Core components

Optical sensors



RGB Sensor

Used for basic color photos, providing 3-band RGB imagery and high-resolution data

Multispectral Sensor

Captures data in multiple bands (4-12 bands), including visible and IR, primarily used for assessing crop health

Hyperspectral Sensor

Offers a much higher number of bands (100+ bands) for detailed analysis, enabling precision analysis.

Thermal Sensor

Detects heat, used for identifying water stress and overall plant health.

Flowchart 2 : Optical Sensors used in Drones.

These cutting-edge technologies make it possible for drones to collect and analyse a wide variety of data across a number of different wavelengths of light, which results in a more in-depth and all-encompassing comprehension of the surrounding environment. RGB sensors are essential for acquiring intricate visual data and serve as the conventional apparatus for traditional photography. RGB, an acronym for Red, Green and Blue, denotes the major colours of light utilised by these sensors to record pictures. These sensors are essential to conventional cameras utilised in drones, generating vibrant, realistic images and movies commonly linked to drone filming. RGB sensors are essential for drones utilised in photography, surveying, and monitoring to collect visual data across many sectors. RGB sensors in drones acquire pictures by amalgamating red, green, and blue light at different intensities, enabling the reproduction of a broad spectrum of colours. This technique is essential for producing high-resolution, colour-accurate photographs from aerial viewpoints. RGB sensors offer significant insights through crisp, detailed pictures in applications such as real estate photography, agricultural monitoring, and environmental surveillance. Visible light, infrared (IR), and ultraviolet (UV) wavelengths are often included in the spectrum of wavelengths that are captured by multispectral targeting sensor systems, which are complex devices that gather data across many spectral bands. These sensors can create high-resolution pictures by processing and analysing this data, which reveals details that are not apparent to the human eye or regular cameras. Because of these capabilities, they are able to carry out increased target recognition, identification, and tracking, which makes them extremely useful in a variety of operational settings (Kerkech *et al*, 2020). Hyperspectral sensors acquire light throughout an extensive spectrum, ranging from visible to near-infrared, frequently dividing the spectrum into several tiny bands. Every pixel in a hyperspectral picture encompasses the complete spectrum of data, facilitating the recognition of distinct "spectral signatures" of various materials or chemicals. Through the analysis of these signals, one may accurately identify, categorise, and monitor the attributes of things, such as differentiating between various plant species or identifying minerals. Drones outfitted with thermal cameras function on a fundamental yet potent principle: they identify and record heat. In contrast to conventional cameras that depend on visible light, thermal cameras detect infrared radiation generated by objects and transform them into pictures. This enables the generation of a comprehensive heat map of the environment, with warmer regions manifesting as brighter areas and colder regions as darker ones. The thermal imaging sensor on these drones has hundreds of tiny sensors capable of detecting even the most subtle temperature variations. The onboard software processes this information, converting it into a visual representation for real-time display on the drone operator's screen (Virtue *et al*, 2021).

Data processing tools

GIS and geospatial integration are the core of spatial data organization and visualization by drones. High-resolution georeferenced imagery is analyzed to create disease distribution maps, vegetation indices (e.g., NDVI, GNDVI), and irrigation heatmaps. The layers can be superimposed with live field data, allowing for precision scouting, input application, and disease monitoring. AI-driven analytics, specifically deep learning and computer vision models enable real-time object detection, anomaly detection, and disease symptom classification. For instance, convolutional neural networks (CNNs) enable the classification of plant disease based on leaf colouration, lesions, or canopy architecture. The models learn and improve over time through feedback loops, with growing predictive accuracy and disease severity scores. Advanced AI workflows allow mission planning to be automated, with drones dynamically creating flight paths based on spatial cues and pre-defined disease hotspots. Precise coverage is ensured through real-time geolocation, and airspace compliance is ensured through geo-fencing systems prescribing and enforcing operation boundaries. Edge AI processing enables in-flight analysis, minimizing latency and allowing for near real-time decision-making in the field. Onboard processors analyze multispectral and thermal inputs to trigger alerts for disease presence or crop stress without human interpretation. Post-flight, data is automatically uploaded to cloud platforms or local servers, where integrated dashboards provide holistic health reports. The dashboards integrate with farm management systems (e.g., ERP, SCADA) through APIs, allowing seamless integration into existing agricultural workflows. Recent work has proven the scalability of these systems. For instance, Komatsu utilized a drone-based AI system through RGB and LiDAR data to automate terrain mapping for agricultural equipment. Similarly, DAC.digital developed a precision agriculture platform that integrates UAV, satellite, and environmental data to forecast crop yields and analyze the impacts of climatic events at a sub-meter spatial resolution.

UAV-Enabled Imaging in Agriculture

The identification of plant diseases has several uses. Various flora and illnesses were found and classified throughout the investigation. Machine learning and deep learning methodologies were employed to detect these illnesses in the leaves, stems, and roots of plants. Detecting plant diseases across diverse species is essential to avert the propagation of ailments and to initiate timely and efficient management techniques.

Crop Surveillance and Condition evaluation

Drones are widely employed in field monitoring, especially in agriculture, to obtain aerial imagery and data from crops. This enables farmers to evaluate crop health, identify pests and diseases, monitor irrigation requirements, analyse soil conditions and ultimately make informed decisions to enhance yield and resource utilisation through precision farming techniques, effectively offering a comprehensive overview of the field to detect issues early and implement targeted interventions. Unmanned Aerial Vehicles (UAVs) outfitted with optical sensors can capture multispectral and thermal data to derive indices of vegetation and water stress, including the Crop Water Stress Index (CWSI) and Normalised Difference Vegetation Index (NDVI), which reflect crop health and water needs (Katsigiannis *et al*, 2016; Lkima *et al*, 2022).

Site-specific weed management refers to the use of tailored control measures exclusively in areas where weeds are present within the crop field, utilising appropriate herbicides based on weed emergence. High accuracies were noted with the multi-spectral camera at various flight altitudes, achieving the highest accuracy of approximately 100% at the 15% weed threshold. Satisfactory results were also recorded for thresholds between 2.5% and 5%, with accuracies exceeding 85% (Lopez-Granados *et al*, 2016). "VIPtero" conducted a flyover of an experimental vineyard in Central Italy, capturing 63 multi-spectral photos during a nearly autonomous 10-minute flight. Images were processed, and vigour maps were generated based on the normalised difference vegetation index. The generated vigour maps demonstrated crop heterogeneity conditions, aligning well with ground-based data. The technology yielded highly promising findings that support its advancement as a tool for precision agriculture in small-scale crops. Drones outfitted with diverse sensors, like multispectral or infrared cameras, may acquire high-resolution photographs of crops. These photos assist farmers in assessing crop health and identifying early indicators of stress, nutritional deficits, or insect infestations. Timely identification of plant diseases is essential for implementing an effective management strategy to prevent disease proliferation and consequent production reduction (Lowe *et al*, 2017). The predominant approach for assessing disease prevalence and severity is visual evaluation through ground scouting. Traditional scouting that entails human assessment is essential for illness validation. Multispectral imagery enhanced watermelon field scouting by facilitating the quick identification of disease foci and areas of concern, achieving early disease detection 20% more frequently than traditional scouting methods with UAV-assisted scouting (Kalischuk *et al*, 2019). Drones, flying at altitudes generally below 500-600 metres, can significantly reduce reliance on meteorological conditions, including cloud cover (Negash *et al*, 2019). The identification of plant diseases is a significant use of drones and has been thoroughly researched. Imaging sensors based on digital (red, blue, and green or RGB), multispectral, hyperspectral, fluorescent, and thermal infrared technologies, when combined with effective algorithms and mounted on drones, can proficiently detect, distinguish, and quantify the severity of symptoms caused by various pathogens in field conditions (Kuska *et al*, 2015). Digital and multi-spectral cameras have been employed to get high-resolution photos in outdoor locations. Drones can create colour-infrared (CIR) photos to facilitate decision-making after RGB photographs. Additional picture types utilised for illness identification encompass visual and near-infrared (V-NIR) images, thermal imaging, and multispectral (MS) images. Field-based photographs have predominantly been produced utilising drones, succeeded by images of leaves and plants (Ampatzidis *et al*, 2017). Agriculturists or consumers acquire photographs of crop foliage via cellphones, drones, or field cameras, which are subsequently preprocessed by resizing, denoising, augmentation, and normalisation to guarantee uniform input quality. Essential characteristics, like leaf pigmentation, markings, and margins, are retrieved, while extraneous regions are obscured. A convolutional neural network (CNN) analyses these characteristics to classify nutritional deficits or illnesses, delivering predictions accompanied by confidence scores. The outcomes, along with therapy suggestions, are presented in an intuitive interface. A feedback loop enables users to validate or amend predictions, hence enhancing the model's accuracy progressively (Ingale, 2024).

Irrigation and Soil Management

Since 1900, global water use has increased sixfold, with approximately 70% of the withdrawn water allocated to agriculture (FAO, 2019; Acharya *et al*, 2021). Ensuring water availability is complicated by climate change, intensive agricultural practices, and challenges impacting the global water system (Lawford, 2015). Recent reports indicate a decline in groundwater levels and an increase in water scarcity in NW India, the US, and central Pakistan (Scanlon *et al*, 2023). UAVs have gained popularity in recent years due to their adaptability and cost-effectiveness, serving as valuable tools across various industries. Unmanned aerial vehicles (UAVs) have demonstrated efficacy across numerous applications; however, their implementation in agriculture, rural development, and specifically in water resource management has been comparatively limited (Yadhav *et al*, 2024). Unmanned aerial vehicles (UAVs) outfitted with LiDAR or multispectral sensors are capable of measuring water depth, while hyperspectral or multispectral cameras can identify pollutants and capture aerial imagery of aquatic environments (Kieu and Law, 2021). These instruments are utilised for mapping the shorelines of water bodies and monitoring long-term changes in both shorelines and water levels. Unmanned aerial vehicle (UAV) platforms equipped with suitable sensors can be utilised to assess water quality, detect algal blooms, and identify sources of pollution. The system is capable of analysing qualitative and quantitative data, such as soil moisture, evapotranspiration and snow cover (Miller *et al*, 2007; Yadav *et al*, 2024a). It provides ultra-high-resolution data unattainable by satellites, rendering it an ideal solution for managing water resources in developing countries with restricted data access. The application of UAV-based canopy temperature measurements has demonstrated efficacy in monitoring crop water status and the soil water stress coefficient (Ks) during the crop growing season (Zhang *et al*, 2023). The canopy temperature serves as a reliable indicator of plant stress, as it consistently reflects water status, plant metabolism, and water utilisation. Thermal images captured using a thermal imaging camera mounted on a micro-UAV demonstrated sufficient sensitivity to distinguish between variations in crop water use resulting from different irrigation management practices and inherent differences in soil properties (Quebrajo *et al*, 2018). A system for in situ surface water quality measurement, assisted by an unmanned aerial vehicle, was developed. A hexacopter was custom-built and outfitted with an open-source electronic sensor platform to measure temperature, electrical conductivity (EC), dissolved oxygen (DO), and pH levels in water (Koparan *et al*, 2018). The UAVi-fmwl offers several advantages, including manoeuvrability and flexibility, high levels of image recognition and analysis automation, elevated recognition accuracy, non-contact operation, cost-effectiveness and independence from water quality requirements. This method is appropriate for measuring water level and surface fluctuations in complex field environments, such as steep mountain slopes, wide rivers, and high-speed flows. It is particularly effective for short-term measurements of water surface fluctuations and urgent changes in water levels, such as those occurring in dammed lakes. This technology applies to hydraulic model experiments and the measurement of fluid surface fluctuations in the oil and metallurgical industries (Gao *et al*, 2019). Soil sampling serves as a critical method for obtaining data necessary for informed decision-making concerning field fertilisation. Drones demonstrate significant efficacy in soil surveys by generating detailed soil maps post-ploughing. These maps facilitate the identification of consistent areas for soil sampling, thereby optimising sample collection and minimising the number of samples needed. Furthermore, the incorporation of wearable augmented reality technology directs users to specific sample locations, thereby improving efficiency (Huuskonen and Oksanen, 2018). Conventional machine learning methods are employed for the identification of plant diseases using drone imagery. The Backpropagation Neural Network (BPNN) served as an early model for utilising spectral data obtained from remote sensing hyperspectral images of tomato plants to assess the severity of infection on plant leaves based on photographic analysis. A five-stage rating system was employed to evaluate the severity of light blight in the photographs and to test the BPNN utilising that data (Abbas *et al*, 2023). The utilisation of high-resolution imagery from drones for capturing images of both healthy and diseased plants has recently advanced. Rice sheath blight represents a significant global disease affecting rice crops. In a study, drones outfitted with digital and multispectral cameras obtained images of research plots containing 67 cultivars and several elite lines. The ground-based normalised difference vegetation index and the image-based normalised difference vegetation index were computed, revealing a strong correlation between the two NDVI data indices. Multispectral images were utilised to quantify varying levels of rice sheath blight disease in field plots, achieving an accuracy exceeding 60%. The findings demonstrate that drones equipped with digital and multispectral cameras represent the most efficient method for identifying rice sheath blight disease in agricultural settings (Martinelli *et al*, 2015).

Precision Planting and Seeding Techniques

Aerial seeding utilising drones is proposed as a prominent technological solution for forest restoration (Castro *et al*, 2023). High-resolution remote sensing imagery enables precise drone seeding at a submeter scale by facilitating the identification and annotation of safe microsites. Drones enable the identification of optimal sites at small spatial scales, characterised by suitable slope, insolation, and soil moisture, thereby serving as effective instruments for enhancing restoration success (Mohan *et al*, 2021). The identification of targeted microsites may subsequently be automated through the application of artificial intelligence (AI). The coordinates of each microsite are subsequently uploaded to the drone, which disperses seeds exclusively at these specified locations. This approach will minimise seed usage by ensuring high precision in seeding at optimal microsites for seedling establishment. The AI system can subsequently be employed to automatically identify target microsites in various regions, thereby facilitating the scalability of drone seeding on a global scale. This enhances existing drone seeding protocols, which distribute seeds uniformly across the area, unlike traditional aerial seeding methods that concentrate on optimal locations at a submeter scale (Castro *et al*, 2024).

Estimation of yield

Unmanned aerial vehicles (UAVs) facilitate low-altitude remote sensing, offering significant advantages such as enhanced flexibility, reduced operational cycles, superior spatial and temporal resolution and cost-effectiveness. Estimating crop yield before harvest is essential for ensuring food security and effectively managing crop development. Unmanned aerial vehicles (UAVs) efficiently and precisely gather data on field crop growth, serving as crucial tools for the collection of agricultural remote sensing information. The rapid advancement of machine learning, particularly deep learning, has led to significant achievements in yield estimation utilising UAV remote sensing data and machine learning techniques (Yuan *et al*, 2024). Extracting images from a drone and analysing them with a deep learning system to identify crop fields and yields in less-developed nations addresses a significant challenge faced by land use–land cover (LULC) studies (Mathivanan and Jayagopal, 2022). Numerous studies have estimated crop yields utilising satellite remote sensing data. For instance, Gomez *et al* (2021) integrated satellite remote sensing with climate data to derive regional wheat yield estimates.

Integration with Machine Learning and AI

Disease Classification Models

Deep learning methods, particularly Convolutional Neural Networks, have shown remarkable efficacy in identifying plant pathogens via image analysis, surpassing traditional machine learning techniques (Kaur *et al*, 2022). The use of CNNs eliminates the need for manual feature extraction by automatically identifying features from both raw and processed images. This skill enables them to effectively manage the variability and complexity of plant diseases. Some studies have demonstrated significant accuracy in plant disease detection through advanced deep learning techniques, including hyperparameter optimisation, ensemble methods utilising AlexNet, ResNet, and VGGNet, and hybrid approaches such as the Multilevel Feature Fusion Network, achieving reported accuracies of 99% (Sunil and Jaidhar, 2024).

With 96% accuracy, a Sequential Convolutional Neural Network (CNN) outperformed conventional machine learning models including SVM, KNN and Random Forest in key metrics including precision, recall, and F1-score according to a study on disease detection in mango and groundnut leaves. Using additional preprocessing methods—including normalisation, histogram equalisation, and rotation—further enhanced the generalisability under diverse field settings, thereby highlighting CNN's potential for real-time disease diagnosis in precision agriculture (Chimate *et al*, 2025).

A recent study introduced a lightweight 2D CNN model designed to classify six disease categories and four healthy categories in crops such as peach, cherry, soybean, and strawberry. The model architecture consists of four convolutional and max-pooling layers, two fully connected layers, dropout, and batch normalisation. It surpassed both heavyweight (VGG16, VGG19, InceptionV3) and lightweight (MobileNet, MobileNetV2, DenseNet, ShuffleNet) transfer learning models, achieving accuracy between 54% and 97%. Although the model features a shallow design, it exhibited robust performance across various datasets and provided practical advantages, including reduced storage needs 3 to 4 times less than transfer learning models—rendering it appropriate for mobile deployment. Visualisation methods such as Grad-CAM and heatmaps were employed to emphasise regions specific to the disease. Minor misclassifications were observed between morphologically similar classes, such as Mn/Mg deficiency and sudden death in soybeans. The study indicates that further optimisation and hybrid models may improve classification robustness under real-world conditions (Prince *et al*, 2024).

Disease severity quantification

A U-Net-based convolutional neural network was developed for pixel-level segmentation of powdery mildew on cucumber leaves utilising visible images, with an emphasis on precise quantification of disease severity. The U-Net model demonstrated a notable enhancement in segmentation accuracy compared to traditional methods like K-means, Random Forest, and GBDT, as evidenced by improvements in Intersection over Union (IoU), Dice coefficient, and pixel accuracy metrics, especially in cases involving distinct mildew lesions. The model exhibited robustness in identifying block-shaped mildew patches, characterised by smoother edge delineation, which is crucial for accurate severity estimation. The method, while exhibiting high performance, necessitates controlled imaging conditions and may encounter difficulties for real-time implementation on portable devices owing to its computational requirements. Furthermore, the generalisation was impacted by imbalanced datasets and a lack of symptom diversity. The model's capacity to quantify disease severity at a detailed level provides important insights for breeders and plant pathologists

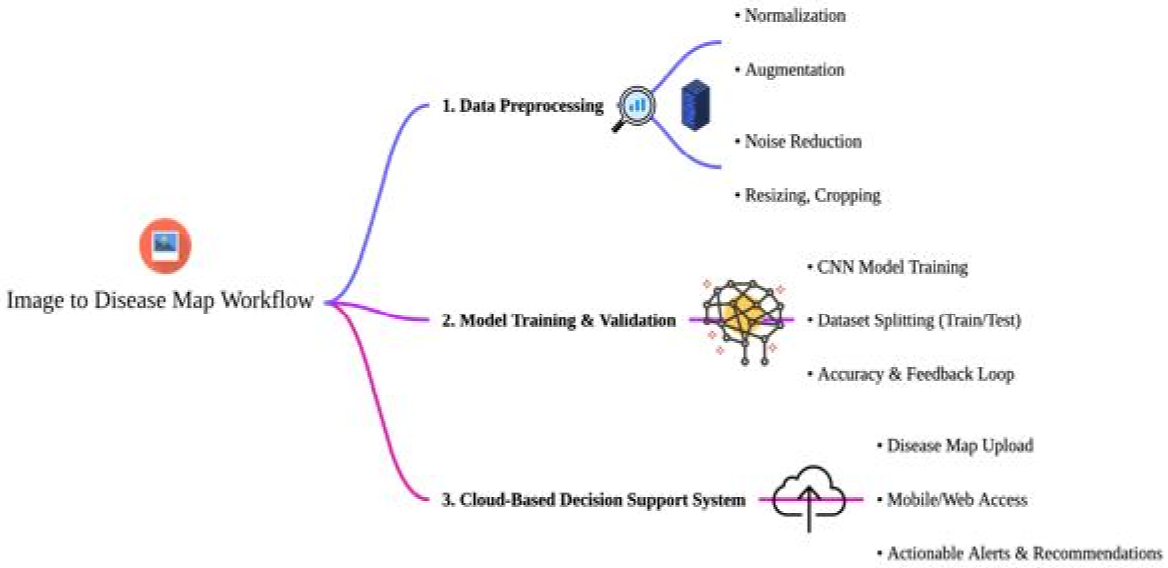


Fig. 1 : Workflow for UAV-based Crop Disease detection.

Table 1 : Comparative Studies on Drone Applications in Agriculture.

Crop	**Camera/Sensor Type**	**Application**	**Result/Findings**	**Accuracy/Performance**	**Reference**
Watermelon	Multispectral camera	Disease detection (Gummy Stem Blight)	Disease foci identified earlier than by traditional scouting	20% earlier disease detection	Kalischuk *et al*. (2019)
Tomato	Hyperspectral sensor	Disease severity prediction (late blight)	Spectral data analyzed by the BPNN model to rate infection severity	High correlation (R^2>0.80) with ground truth	Abbas *et al*. (2023)
Rice	Digital & Multispectral camera	Detection of Sheath Blight	Image-based NDVI correlated strongly with ground-based NDVI to assess disease levels	>60% classification accuracy	Martinelli *et al*. (2015)
Mixed crops	RGB & Multispectral + CNN	Disease & nutrient deficiency detection	Deep learning identified symptoms from leaf images with feedback for continuous model improvement	Accuracy improves over time with feedback loop	Ingale (2024)
Wheat	Satellite + UAV remote sensing	Yield prediction (ML-based)	Combined UAV and climate data to model regional wheat yield	High correlation with observed yield (R^2>0.85)	Gomez *et al*. (2021)
Cotton	UAV Hyperspectral imaging (400–995 nm)	Cotton Verticillium Wilt detection	Incidence detection models at the leaf scale achieved a peak classification accuracy of 85.83%, which is about 10% higher than traditional methods without feature selection.	The severity detection models showed improved precision as disease severity of damage increased, with accuracy ranging from 46.82% to 93.10%.	Li *et al*. (2025)
Potato	UAV Hyperspectral imaging	Potato Virus Y & Blackleg detection	YOLOv5s model detected infected plants through dimensionality reduction	mAP@0.50: 0.85 (blackleg), 0.82 (PVY)	Jia *et al*. (2024)
Maize	UAV RGB + YOLOv5	Plant detection and counting	YOLOv5 achieved best performance under realistic field conditions	mAP@0.5: 82.8% (3-leaf), 86.3% (7-leaf)	Lu *et al*. (2024)
Barley	High-Throughput Enzyme Activity Signature Profiling and Multispectral Imaging + ML	Powdery mildew resistance screening and detection	Plant resistance phenotyping with multispectral imaging in high-throughput	95.0% overall accuracy	Kuska *et al*. (2018)

NDVI = Normalized Difference Vegetation Index, BPNN = Backpropagation Neural Network, CIR = Color-Infrared, EC/DO/pH = Electrical Conductivity, Dissolved Oxygen, pH.

seeking to accurately evaluate infection levels (Lin *et al*, 2019).

Limitations and Challenges

Plant pests and diseases have resulted in considerable social, post-harvest and economic losses in worldwide agricultural output, especially as a consequence of climate change. Numerous methodologies have been investigated for the detection, monitoring, and assessment of plant diseases, emphasizing non-invasive technology. Many models employ pre-trained CNNs; however, their ensemble can enhance accuracy in the identification and classification of various plant diseases. The SVM classifier is a widely utilized machine learning model, and evaluating proposed models against other classifiers or integrating their parameters is an emerging trend. Conventional methods are inadequate because of the diversity of plant species and disease categorization; however, transfer learning can enhance model complexity and efficacy. Hyperspectral technology has garnered attention in recent years. Sustainable management of plant pests and diseases integrates insights into plant disease epidemics, enhances plant health, and improves crop quality while conserving natural resources. Challenges in plant pest control encompass fluctuations in lighting conditions, stages of disease progression, restricted access to diverse datasets, computational difficulties in processing extensive datasets, real-time disease detection, environmental factors affecting detection accuracy, integration of multi-modal data sources, creation of robust models, climate change impacts on plant diseases, and the incorporation of IoT devices, drones, and mobile applications (Shafik *et al*, 2023). Costs of the data acquired by drones can be from 10 to 100 times more expensive per hectare than costs of satellite data (Negash *et al*, 2019). UAV-based precision irrigation scheduling in field crops is still at the beginning stage though improving water productivity of field crops is a major concern (Yadav *et al*, 2024).

Future Prospects

The science is becoming deûned, the concepts of disease measurement are being explored, and many familiar sources of error in visual rating have been identiûed. In recent decades, significant progress has been made in the assessment of plant diseases and the application of remote sensing technologies for disease management, especially in the areas of image analysis and, more recently, hyperspectral and ultra-spectral imaging. These factors are expected to assume a more significant role in disease assessment. The latest generation features sensor-equipped drones that precisely identify plant diseases in their initial stages, facilitating the implementation of appropriate management strategies to prevent future outbreaks. We highlighted several sensors that can be integrated into drone platforms, such as digital, multispectral, hyperspectral, thermal, and fluorescence sensors. Hyperspectral sensors exhibit greater robustness compared to digital and multispectral sensors. In contrast, thermal sensors are operable both day and night, offering enhanced insights into plant status relative to alternative sensor types. Third, various types of drones and their operational mechanisms were presented. VTOL and fixed-wing drones possess a greater capacity for carrying cameras and sensors compared to rotary-wing drones. Consequently, VTOL and fixed-wing drones exhibit extended flight durations and the capability to cover extensive areas. Nonetheless, these types are costly and may experience difficulties during hovering. Data fusion approaches can enhance the detection procedures for activities including crop monitoring and plant categorisation. The development of precise, real-time, reliable, and autonomous drone-based systems for detecting plant diseases has gained significance in contemporary agriculture. These systems necessitate advanced and efficient algorithms to tackle challenges including variable illumination, increasing diseases, occlusion, and changing perspectives. To achieve enhanced agricultural yields, the integration of advanced technologies, including drone systems and deep learning frameworks, is essential. The accessibility of agricultural data represents a significant challenge that requires attention. Building realistic datasets requires the collection of supplementary data or the development of sophisticated algorithms utilising generative deep learning architectures.

Conclusion

The integration of Unmanned Aerial Vehicles (UAVs) into plant disease detection systems is a major revolution in precision plant pathology. This review highlights the potential of UAVs, integrated with multispectral, hyperspectral, thermal, and RGB sensors, to obtain high-resolution, real-time monitoring over large agricultural fields. These platforms offer scalable and non-destructive alternatives to the replacement of conventional scouting practices and laboratory diagnostics to enable early detection, classification, and quantification of crop diseases before severe visual symptoms develop. The integration of UAVs and artificial intelligence—namely convolutional neural networks (CNNs) and U-Net-based models—has been a key breakthrough in disease detection, spatial mapping and disease severity assessment. In addition, UAV-based systems support multi-purpose usage scenarios beyond disease detection, including water stress analysis, soil health mapping, yield estimation and precision seeding. These are supplemented by their linkage with geospatial software and cloud-based farm management systems to facilitate a smooth transition from data acquisition to actionable decision-making on the ground. Workflow automation, personalization of interventions, and enabling site-specific crop management are key to lowering productivity and facilitating agricultural sustainability. Regardless of this, there are still challenges. Exorbitant initial costs, sensor unavailability under canopy layers, computational requirements for real-time processing, limited availability of annotated datasets, and UAV flying restrictions due to regulations are still significant barriers. Variability in illumination, phenological variation in crops, and manifestations of disease symptom onset could also influence generalization and model accuracy. Even with these challenges, the future for UAV-based plant disease monitoring is bright. With decreasing algorithm size, datasets becoming more representative, and drone hardware becoming less expensive but autonomous, mass adoption becomes more and more viable even for small-scale farmers. The future research agenda must include strong data fusion algorithms, edge computing for real-time decision-making, and standards for UAV-based disease monitoring. In general, UAVs are not technologies but drivers for the revolution of plant protection and digital agriculture.

Authors' contributions

This review was carried out in collaboration among all authors. All authors read and approved the final manuscript and there is no conflict of interest to declare.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript

References

Abbas, A., Zhang Z., Zheng H., Alami M.M., Alrefaei A.F., Abbas Q., Naqvi S.A.H., Rao M.J., Mosa W.F.A., Abbas Q., Hussain A., Hassan M.Z. and Zhou L. (2023). Drones in Plant Disease Assessment, Efficient Monitoring, and Detection: A Way Forward to Smart Agriculture. *Agronomy*, **13(6)**, 1524. https://doi.org/10.3390/agronomy13061524

Abdullah, H.M., Mohana N.T., Khan B.M., Ahmed S.M., Hossain M., Islam K.S. and Ahamed T. (2023). Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. *Remote Sensing Applications: Society and Environment*, **32**, 100996.

Acharya, B.S., Bhari M., Bini F., Pizarro A., Perks M., Joshi D.R. and Sharma S. (2021). Unmanned aerial vehicles in hydrology water management: Applications, challenges, perspectives. *Water Resour. Res.*, **57**, 1–33. https://doi.org/10.1029/2021WR029925

Ahirwar, S., Swarnkar R., Bhukya S. and Namwade G. (2019). Application of Drone in Agriculture. *Int. J. Curr. Microbiol. Appl. Sci.*, **8(1)**, 2500–2505.

Ampatzidis, Y., De Bellis L. and Luvisi A. (2017). iPathology: Robotic Applications and Management of Plants and Plant Diseases. *Sustainability*, **9(6)**, 1010. https://doi.org/10.3390/su9061010

Castro, J., Alcaraz Segura D., Baltzer J.L., Amorós L., Morales Rueda F. and Tabik S. (2024). Automated precise seeding with drones and artificial intelligence: A workflow. *Restoration Ecololgy*, **32(5)**, e14164. https://doi.org/10.1111/rec.14164

Castro, J., Morales Rueda F., Alcaraz Segura D. and Tabik S. (2023). Forest restoration is more than firing seeds from a drone. *Restoration Ecology*, **31(1)**, e13736. https://doi.org/10.1111/rec.13736

Celen, I.H., Önler E. and de Lyon L.B. (2020). Drone Technology in Precision Agriculture. Chapter in Academic Studies in Engineering Sciences, Kurt, H. I. (ed.) Livre de Lyon, 2020, 121–140.

Chimate, Y., Patil S., Prathapan K., Patil J. and Khot J. (2025). Optimized sequential model for superior classification of plant disease. *Scientific Reports*, **15(1)**, 3700. https://doi.org/10.1038/s41598-025-86427-8

Dileep, M.R., Navaneeth A.V., Ullagaddi S. and Danti A. (2020). A Study and Analysis on Various Types of Agricultural Drones and its Applications. *2020 Fifth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, 181–185. https://doi.org/10.1109/ICRCICN50933.2020.9296195

FAO (2019). FaoStat. Food Agriculture Organization of the United Nations. http://faostat.fao.org/

Gao, A., Wu S., Wang F., Wu X., Xu P., Yu L. and Zhu S. (2019). A Newly Developed Unmanned Aerial Vehicle (UAV) Imagery based Technology for Field Measurement of Water Level. *Water*, **11(1)**, 124. https://doi.org/10.3390/w11010124

Gomez, D., Salvador P., Sanz J. and Casanova J.L. (2021). Modelling wheat yield with antecedent information, satellite and climate data using machine learning methods in Mexico. *Agricult. Forest Meteorol.*, **300**, 108317. https://doi.org/10.1016/j.agrformet.2020.108317

Gustafsson, J., Cederberg C., Sonesson U. and Emanuelsson A. (2013). The methodology of the FAO study: Global Food Losses and Food Waste-extent, causes and prevention"-FAO, 2011.

Hafeez, A., Husain M.A., Singh S.P., Chauhan A., Khan M.T., Kumar N. and Soni S.K. (2023). Implementation of drone technology for farm monitoring & pesticide spraying: A review. *Information Processing in Agriculture*, **10(2)**, 192-203.

Huuskonen, J. and Oksanen T. (2018). Soil sampling with drones and augmented reality in precision agriculture. *Computers and Electronics in Agriculture*, **154**, 25–35. https://doi.org/10.1016/j.compag.2018.08.039

Ingale, S. (2024). Identification of nutritional deficiency and disease prediction of crops using deep learning: A review. *Int. J. Scient. Res. Comput. Sci. Engg.*, **5(10)**.

Jia, T., Smigaj M., Kootstra G. and Kooistra L. (2024). Detection of Diseased Potato Plants with UAV Hyperspectral Imagery. *2024 14th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, 1–5. https://doi.org/10.1109/WHISPERS65427.2024.10876424

Kalischuk, M., Paret M.L., Freeman J.H., Raj D., Da Silva S., Eubanks S., Wiggins D.J., Lollar M., Marois J.J., Mellinger H.C. and Das J. (2019). An Improved Crop Scouting Technique Incorporating Unmanned Aerial Vehicle-–Assisted Multispectral Crop Imaging into Conventional Scouting Practice for Gummy Stem Blight in Watermelon. *Plant Disease*, **103**(7), 1642–1650. https://doi.org/10.1094/PDIS-08-18-1373-RE

Katsigiannis, P., Misopolinos L., Liakopoulos V., Alexandridis T.K. and Zalidis G. (2016). An autonomous multi-sensor UAV system for reduced-input precision agriculture applications. In 2016 24th Mediterranean Conference on Control and Automation (MED). IEEE, pp. 60–64.

Kaur, P., Harnal S., Tiwari R., Upadhyay S., Bhatia S., Mashat A. and Alabdali A.M. (2022). Recognition of Leaf Disease Using Hybrid Convolutional Neural Network by Applying Feature Reduction. *Sensors*, **22(2)**, 575. https://doi.org/10.3390/s22020575

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

Kieu, H.T. and Law A.W.-K. (2021). Remote sensing of coastal hydro-environment with portable unmanned aerial vehicles (pUAVs) a state-of-the-art review. *J. Hydro-Environ. Res.*, **37**, 32–45. https://doi.org/10.1016/j.jher.2021.04.003

Koparan, C., Koc A., Privette C. and Sawyer C. (2018). *In situ* Water Quality Measurements using an Unmanned Aerial Vehicle (UAV) System. *Water*, **10(3)**, 264. https://doi.org/10.3390/w10030264

Kuska, M.T., Behmann J., Großkinsky D.K., Roitsch T. and Mahlein A.-K. (2018). Screening of Barley Resistance Against Powdery Mildew by Simultaneous High-Throughput Enzyme Activity Signature Profiling and Multispectral Imaging. *Front. Plant Sci.*, **9**, 1074. https://doi.org/10.3389/fpls.2018.01074

Kuska, M., Wahabzada M., Leucker M., Dehne H.-W., Kersting K., Oerke E.-C., Steiner U. and Mahlein A.-K. (2015). Hyperspectral phenotyping on the microscopic scale: Towards automated characterization of plant-pathogen interactions. *Plant Methods*, **11(1)**, 28. https://doi.org/10.1186/s13007-015-0073-7

Lawford, R. (2015). Adapting to Climate Change: The Role of Science and Data in Responding to Opportunities and Challenges in the Water-Soil-Waste Nexus. United Nations University Institute for Integrated Management of Material Fluxes and of Resources (UNU-FLORES).

Li, W., Liu L., Li J., Yang W., Guo Y., Huang L., Yang Z., Peng J., Jin X. and Lan Y. (2025). Spectroscopic detection of cotton Verticillium wilt by spectral feature selection and machine learning methods. *Front. Plant Sci.*, **16**, 1519001. https://doi.org/10.3389/fpls.2025.1519001

Lin, K., Gong L., Huang Y., Liu C. and Pan J. (2019). Deep Learning-Based Segmentation and Quantification of Cucumber Powdery Mildew using Convolutional Neural Network. *Front. Plant Sci.*, **10**, 155. https://doi.org/10.3389/fpls.2019.00155

Lkima, K., Salcedo F.P., Mabrouki J. and Aziz F. (2022). Precision Agriculture: Assessing Water Status in Plants Using Unmanned Aerial Vehicle. In: Azrour, M., Irshad A. and Chaganti R. (Eds.), *IoT and Smart Devices for Sustainable Environment* (pp. 139–153). Springer International Publishing. https://doi.org/10.1007/978-3-030-90083-0_11

Lopez-Granados, F., Torres-Sánchez J., Serrano-Pérez A., De Castro A.I., Mesas-Carrascosa, Fco.-J. and Peña J.-M. (2016). Early season weed mapping in sunflower using UAV technology: Variability of herbicide treatment maps against weed thresholds. *Precision Agriculture*, **17(2)**, 183–199. https://doi.org/10.1007/s11119-015-9415-8

Lowe, A., Harrison N. and French A.P. (2017). Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. *Plant Methods*, **13**, 80.

Lu, C., Nnadozie E., Camenzind M.P., Hu Y. and Yu K. (2024). Maize plant detection using UAV-based RGB imaging and YOLOv5. *Front. Plant Sci.*, **14**, 1274813. https://doi.org/10.3389/fpls.2023.1274813

Martinelli, F., Scalenghe R., Davino S., Panno S., Scuderi G., Ruisi P., Villa P., Stroppiana D., Boschetti M., Goulart L.R., Davis C.E. and Dandekar A.M. (2015). Advanced methods of plant disease detection. A review. *Agron. Sust. Develop.*, **35(1)**, 1–25. https://doi.org/10.1007/s13593-014-0246-1

Mathivanan, S.K. and Jayagopal P. (2022). Utilizing satellite and UAV data for crop yield prediction and monitoring through deep learning. *Acta Geophysica*, **70(6)**, 2991–3004. https://doi.org/10.1007/s11600-022-00911-7

Miller, G.R., Baldocchi D.D., Law B.E. and Meyers T. (2007). An analysis of soil moisture dynamics using multi-year data from a network of micrometeorological observation sites. *Advances in Water Resources*, **30(5)**, 1065–1081. https://doi.org/10.1016/j.advwatres.2006.10.002

Mohan, M., Richardson G., Gopan G., Aghai M.M., Bajaj S., Galgamuwa G.A.P., Vastaranta M., Arachchige P.S.P., Amorós L., Corte A.P.D., de-Miguel S., Leite R.V., Kganyago M., Broadbent E.N., Doaemo W., Shorab

M.A.B. and Cardil A. (2021). UAV-Supported Forest Regeneration: Current Trends, Challenges and Implications. *Remote Sensing*, **13(13)**, 2596. https://doi.org/10.3390/rs13132596

Munjal, D., Singh L., Pandey M. and Lakra S. (2023). A systematic review on the detection and classification of plant diseases using machine learning. *Int. J. Software Innovation (IJSI)* **11**, 1–255. doi: 10.4018/IJSI.315657

Nazarov, P.A., Baleev D.N., Ivanova M.I., Sokolova L.M. and Karakozova M.V. (2020). Infectious plant diseases: Etiology, current status, problems and prospects in plant protection. *Acta naturae*, **12(3)**, 46.

Scanlon, B.R., Fakhreddine S., Rateb A., De Graaf I., Famiglietti J., Gleeson T., Grafton R.Q., Jobbagy E., Kebede S., Kolusu S.R., Konikow L.F., Long D., Mekonnen M., Schmied H.M., Mukherjee A., MacDonald A., Reedy R.C., Shamsudduha M., Simmons C.T. and Zheng C. (2023). Global water resources and the role of groundwater in a resilient water future. *Nat. Rev. Earth Environ.*, **4(2)**, 87–101. https://doi.org/10.1038/s43017-022-00378-6

Shafik, W., Tufail A., Namoun A., De Silva L.C. and Apong R.A.A.H.M. (2023). A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends. *IEEE Access*, **11**, 59174–59203. https://doi.org/10.1109/ACCESS.2023.3284760

Shaikh, T., Rasool T. and Lone F.R. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comput. Electron. Agric.*, **198**, 107119.

Sunil, C.K. and Jaidhar C.D. (2024). An Efficient Infectious Disease Detection in Plants Using Deep Learning. In : Das, H., Acharya A.A. and Li K.-C. (Eds.), *Intelligent Technologies* (Vol. 1167, pp. 55–74). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-5204-1_3

Virtue, J., Turner D., Williams G., Zeliadt S., McCabe M. and Lucieer A. (2021). Thermal Sensor Calibration for Unmanned Aerial Systems using an External Heated Shutter. *Drones*, **5(4)**, 119. https://doi.org/10.3390/drones5040119

Yadav, M., Vashisht B.B., Jalota S.K., Jyolsna T., Singh S.P., Kumar A., Kumar A. and Singh G. (2024). Improving Water Efficiencies in Rural Agriculture for Sustainability of Water Resources: A review. *Water Resources Management*, **38(10)**, 3505–3526. https://doi.org/10.1007/s11269-024-03836-6

Yadav, M., Vashisht B.B., Vullaganti N., Kumar P., Jalota S.K., Kumar A. and Kaushik P. (2024). UAV-enabled approaches for irrigation scheduling and water body characterization. *Agricult. Water Manage.*, **304**, 109091. https://doi.org/10.1016/j.agwat.2024.109091

Yuan, J., Zhang Y., Zheng Z., Yao W., Wang W. and Guo L. (2024). Grain Crop Yield Prediction using Machine Learning based on UAV Remote Sensing: A Systematic Literature review. *Drones*, **8(10)**, 559. https://doi.org/10.3390/drones8100559