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REVIEW ARTICLE

Trends in Biotechnology and Plant Sciences

Role of Remote Sensing and GIS in Plant Disease Monitoring

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Abstract

Food Security is at risk because of pest epidemics, especially where agriculture is the main activity. These biotic stressors cause poor crop productivity, poor input utilization, and result in massive economic losses. The widely used conventional approaches-manual surveys and observation of the symptoms- are slow, spatial, and not effective during the initial phases of infection and especially in circumstances of altering climatic conditions. The outcomes of reactive management are often over spraying and damages to the environment. The combination of Remote Sensing (RS) and Geographic Information Systems (GIS) has transformed plant disease surveillance to the point of being dynamic, real time and spatially large scale. The subtle physiology differences in crops are sensed by means of RS platforms, such as satellites, UAVs, and ground sensors. GIS is an analysis tool used to manage spatial and attribute data and then visualize disease, evaluate risk and aid decision-making. The review will refer to the RS-GIS technologies, methods, applications and restrictions. The recent developments in the management of plant diseases exemplify the multi-sensor-AI integration and AI-based diagnosis combination, achieving complete multifaceted, early-detection and discerning treatment procedures (Seralathan & Edward, 2024). Such innovative observational methods like the application of artificially intelligent detection, UAV surveys, and geostatistical modeling increase early detection and bespoke responses. The recent ones are IoT sensor networks, cloud computing, and mobile decision-support systems in sustainable, data-driven agriculture.

KEYWORDS
Remote sensing (RS), Geographic information systems (GIS), Plant pathology, Disease detection, UAV, Vegetation indices, Spatial epidemiology, Precision agriculture, Crop monitoring, AI in Agriculture

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1 | INTRODUCTION

The rising incidence of crop diseases and pest outbursts worsen the world food security since it causes yield, financial losses, and ecological imbalance. The presence of biological stressor, such as fungi, bacteria, viruses, and nematodes deters the productivity and input efficiency, particularly in developing economies where the agricultural sector is one of the key stakes of the economy (Sabtu et al., 2018). The outbreak of diseases has also been caused by emergence of climate change, international trade, and land-use alteration, which should be adequately monitored. The traditional methods (hand field inspection, hand symptom detection) of disease scouting involve time-consuming steps, are spatially limiting, and they do not offer detection of infections early enough. Besides, due to the lack of elaborate diagnosis, excessive exposure to pesticides is made, resistance develops, and the use of broad-spectrum chemical treatment promotes the destruction of the environment (Li et al., 2024; Okole et al., 2024) and requires a more sophisticated approach.

Geospatial technologies have recently been considered as a game changer in proactive disease management strategies particularly Remote Sensing (RS) and Geographic Information Systems (GIS). These RS platforms such as satellites, UAVs, and ground-based sensors collect spectral, thermal and radar data that detects the minute physiological changes in crops that precede noticeable symptoms. GIS contributes to this by integrating spatial and environmental information to display the spreading of the disease and risk areas and decision-making. For example, satellite data obtained through NDVI can enable the studio to establish the existence of chlorophyll in infected plants, and the GIS overlaps of the soil moisture/temperature data can be used to determine areas of the specific disease heat points (Palaniyandi, 2012). Such technologies along with agriculture have also been applied in the modeling of infectious diseases characterised by vectors much like malaria and hence their multidisciplinary utility in addressing complex ecological and health problems (Zhang & Kovacs, 2012).

The review will accomplish three objectives: (1) systematic generalization of the methods applied to the monitoring of plant diseases, including Remote Sensing (RS) and Geographic Information Systems (GIS), its potential to early detect the disease and its severity, and the spatial epidemiology of planted crops; (2) niche technological advancements, such as analytics driven by AI, surveillances by UAV, and platforms based on clouds, their limitations, and why these tools can be used on a spatial scale; and (3) summarizing the case studies and trends in emerging practices that can transform plant disease management into a sustainable agricultural and dietary provision. Such machine learning algorithms as support vector machines (SVMs), random forests (Rfs), and the like have been comprehensively evaluated in terms of their effectiveness in working with remotely sensed datasets to track crop diseases, proposing potentially scalable applications in large-scale agricultural infrastructures (Zhang et al., 2024). The gaps in the knowledge may be filled with the current review, conditioning future research and the implementation of the exact knowledge in the precision agriculture.

Remote Sensing (RS)

The term Remote Sensing (RS) can be thought of as the gathering of information on objects or processes that involves no form of physical interaction with the object (usually in the form of measuring reflected or emitted components of the electromagnetic spectrum). Being able to trace the health of crops 24/7, including to take note of biotic and abiotic constraints into consideration and approximate the harvests, RS has acquired a critical role in the field of agriculture. The satellite (e.g., Landsat, Sentinel-2, MODIS, NOAA-AVHRR), air (e.g., aircraft, drone) and ground-based sensors (e.g., spectroradiometers, tractor-mounted, sensors) will be included in the RS platforms (Palaniyandi, 2012; Sishodia et al., 2020).

These platforms have different spatial, spectral and temporal resolutions in all of them. Extensive use of the satellite is explained by the level of the coverage which covers regional and national monitoring capabilities of satellite, whereas the extensive use of UAVs and drones is determined by the high resolutions they obtain which may be useful at the field level. These types of platforms are accompanied by surface sensors that collect the measures of the situational and real-time canopy contrast, temperature and wetness.

The sensors which can be used in detecting the diseases in the plant may include the following:

Optical sensors: In the shape of RGB, multispectral, hyperspectral cameras, the discrepancy in the structure and biochemical arrangement and coloration of the leaf is identified.

Thermal sensors: monitoring of canopy temperature and transpiration rates are used and such values change when there is an onset of the disease.

Radar sensors: Synthetic Aperture Radar (SAR) is not weather dependent as it can help to map a specific land and inform about the soil moisture.

The major components related to the disease identification and the stress measure in the RS data include vegetation indices. The most popular index is Normalized Difference Vegetation Index (NDVI), since this index measures the intensity of vegetation by measuring reflectance near IR and red spectrum. NDVI varies between negative one to positive one with lower the value the healthier or less stressed it is. RGB indices like VARI and MGRVI give similar accuracy of stress classification at a reduced cost as compared to multispectral sensor, hence it is cost-effective in palm cultivations (Panthakkan, 2025). The developments in plant disease management over the past years tell that the use of this multisensor data fusion approach along with AI-based diagnostics represents an end-to-end solution to both simultaneous pathogen identification and targeted therapy (Negi & Anand, 2024b). Other indices In addition to them are:

- **Green Non descriptive Vegetative Indication (GNDVI):** flora reaction to the prosperity enrichments and chlorophyll in hiding.
- **RENDVI (Red Edge NDVI):** it proved useful in detection of the early symptoms in vegetation covered type which indicated heavy green vegetation.

- **NDWI (Normalized Difference Water Index)** is used to determine the degree of stress that exists in water and water moisture.
- **Thermal indices:** they are gauged with the help of infrared reading to notice abnormalities of canopy temperatures. Thermal cameras attached to drones also identify very crucial infestations since the operator can identify patterns depending on temperature changes to ensure they take early action in order to avoid applying any pesticides (DataIntelo, 2025).

Certain crops infected with Ralstonia solanacearum, Phytophthora infestans and Xanthomonas spp are the various examples of pre-symptomatic changes that define the RS technology. To exemplify, (Abdulridha et al., 2019) study was able to detect citrus canker in 96 percent of the cases at an early stage of canker development when applying hyperspectral UAV imaging. Likewise, Spectral reflectance can also be used to predict physiological stress before the occurrence of visual infection in cucumber plants because of bacterial wilt (Sabtu et al., 2018).

Geographic Information System (GIS)

Geographic information systems (GIS) describe computerized systems to record, store, analyses and present spatially as well as attribute information. GIS plays a pivotal role in the field of plant pathology to display the spread of a disease and it models risk and decision making. The GIS platforms such as ArcGIS, GRASS, MapInfo, IDRSI offer a sequence of sets of analytic tools which comprise of buffering, overlay analysis, Taylor decomposition and model sampling (Palaniyandi, 2012).

GIS uses many modules with data to create detailed maps of disease distribution i.e. coupling the data types such as crop type, soil characteristics, elevation, temperature, humidity, disease incidences. Among the applications of such maps, there is the identification of hotspots, disease outbreaks monitoring and wise use of resources. To illustrate, GIS has demonstrated the production of nematode risk maps in various parts of Brazil and this has saved the costly chemical treatment plans. The fertilizer aided by GIS technique in New Zealand immensely controlled the environmental runoff and the utilization of nutrients. In Malaysia, GIS usage included serving paddy plantation as well as oil palm with monitoring facilities of an Internet type and the possibility of integrating spatial data (Sabtu et al., 2018).

Spatial epidemiology can also be done using GIS based on the indices generated by RS which along with the environmental factors could provide indicators of the outbreaks. The water bodies are neighborhoods, presence of buffer zones around where the vegetation of the vectors lie and presence of cover are discussed to understand the level of risk. Such integration has the potential to develop early warning and decision-making platforms that will target certain intervention and improve the non-sustainability of agriculture.

Remote Sensing in Plant Disease Detection

Remote sensing has become the handy instrument of discovering plant diseases during its various growth stages. RS has the prospect of documenting spectral, thermodynamic and structural vegetation response which aids in early diagnosis, assessment of the severity and spatial disease outbreaks. Special interest can be attributed to RS in proactive disease manage-ment because the physiological effects of stress are measurable earlier than the visual ones. Infectious disease ecology has been demonstrated to be a key contributor through remote sensing, and as a means of bridging the gap between environmental processes, like vegetation density and the presence of water bodies, hemodynamics, and trends in pathogen dissemination, resulting in disease outbreak predictive modeling of zoonotic diseases (Teitelbaum et al., 2024).

Early Detection of Diseases

This is because early diagnosis is of high significance in mitigating the loss of the crops and prevention of further transmission of the diseases. RS technologies like hyperspectral and multispectral imaging can identify such minor changes in leaf reflectance in leaves with degraded pigments, water deficient cells, or an adaptation needed to survive in stressful conditions. These changes take place before the obvious signs and thus, they can be addressed before they happen.

To give an example, (Abdulridha et al., 2019) demonstrated that the use of hyperspectral UAV imaging and machine learning enabled them to detect citrus canker at its initial stages with the 96 percent degree of accuracy. Similarly, Di Gennaro was researching the NDVI indicators correlation with the severity of the grapevine leaf stripe disease, the stages of which can be predicted and diagnosed early and locally treated (Di Gennaro et al., 2016). East Africa has been successfully utilized in predicting occurrence of wheat rust using the NDVI and GIS model where it was applied in predicting future outbreaks and fungicides applied in the region as opposed to upstream regions where it was not applied which lost a lot in terms of outputs (Zhang & Kovacs, 2012).

Multispectral cameras on UAVs indicated developments of rice blast in Southeast Asia early in the process, therefore allowing them to respond to it before the disease could cause significant damage (Tsouros et al., 2019). The shown case studies show a possibility of RS to be applied in the early disease detection in multiple crops and crop systems and even geographical regions. Current studies show that plant disease can be noticed through the UVAs to conduct multispectral imaging along with a highly trained learning algorithm to recognize early indicators at least 10 days before the visible manifestations with greater than 93% accuracy rate and on alternative crops.

Disease Severity Estimation

The RS can be also applied to estimation of the disease by measuring its intensity beyond its detection threshold. The level of infection is assessed with the help of indices of disease, viral specific viral indices (SDIs), SAVI and NDVI. The resultant canopy thermal changes due to distorted transpiration that resulted in temperature anomalies can be detected using thermal images and detection of biochemical variation in chlorophyll, carotenoids and water can be provided using hyperspectral information. Manageability of MLVI and H VSI, being subcategories of machine-learning-optimized hyperspectral index, has allowed the detection of crop stress 10-15 days ahead of the traditional tools, and lastly, critical wavelength bands in NIR and SWIR have been employed to enhance sensitivity classification (Seralathan, 2025).

The RS data set is used to establish the seriousness of a disease based on the machine learning algorithm models, including the Convolutional Neural Networks (CNN), Random Forest (RF), and logistic regression. The models look at patterns of the spectra and spatial characteristics to distinguish between healthy, mildly infected plants as well as severely infected plants. The The swarm intelligence optimized Enhanced SAO CNN model has been repeatedly proved to provide better performance in dynamic classification of pests and diseases with 94% accuracy in the field trials. The optimization of the UAV flight paths and optimisation of the sensor data fusion it is the mechanism (Chu & Bao, 2025). Such an example is GeoAgriGuard with the accuracy of 97.81% and F1-score of 96.27% depending on the disease classification because it utilizes ResNet, Transformer, DenseNet, and AutoEncoders (Sharada et al., 2025).

Such quantitative estimates are advantageous in precision agriculture where application of variable-rate fungicides is possible, resources are used at optimum levels, and impact on environment can be minimized. In aquatic animal health, the use of emerging technologies such as hyperspectral imaging and AI- based diagnostics is gaining momentum and therefore represents a demonstration of the cross-disciplinary capability of RS and GIS in monitoring biotic stressors in ecosystems (Bohara et al., 2024). This has recently become possible in edge-cloud computing in order to deploy deep neural networks (DNNs) with transfer learning, capable of real-time detection of plant diseases, greatly enhancing the scalability and lessening latency in processing the remote sensing unit data (Mohammed et al., 2024).

UAV and Drone-Based Disease Monitoring

The revolution in the monitoring of the occurrences of diseases at the field level has been brought about by the high-resolution pictures, flexibility of drones and Unmanned Aerial Vehicle (UAV) based collection of data as well as the affordability. A number of surveys could be performed during a growing season by implementation of UAVs, which ultimately gives cm-scale imagery and is thus appropriate in smallholder farms and their inaccessible areas. With convolutional neural networks (CNNs) and Transformers being the most common deep learning architectures, autonomously monitoring crop health, based on unmanned aerial vehicle (UAV) imagery has now become commonplace and as a result is able to provide real-time surveillance capabilities and reduce the need of manual labor to conduct such inspections (Fig. 1) (Negi & Anand, 2024a).

Many diseases have been tracked with the help of UAVs equipped with multispectral, hyperspectral and infrared sensors. GIS and thermal image were used in America to track the spread of a sobering disease called citrus greening which was a bacterial disease of citrus orchards. CNNs, as an example of deep learning models, have also been used in conjunction with UAV-based remote sensing to obtain a high level of up to 97% accuracy in crop disease and pest detection even under a complex field setting (Zhu et al., 2024). The combination of hyperspectral RS and GIS was demonstrated successfully in Europe, where fungicide was optimally used against potato late blight using less chemical and achieving a healthier crop (Calderón et al., 2015). The methodology described by (Ren et al., 2025) of monitoring the infestation of cotton aphids incorporates multi-source data fusion in unmanned aerial vehicle (UAV), such as thermal imaging and multispectral sensing, to increase the detection efficiency by an approximately 20 per cent figure compared to the traditional approach to detection systems.

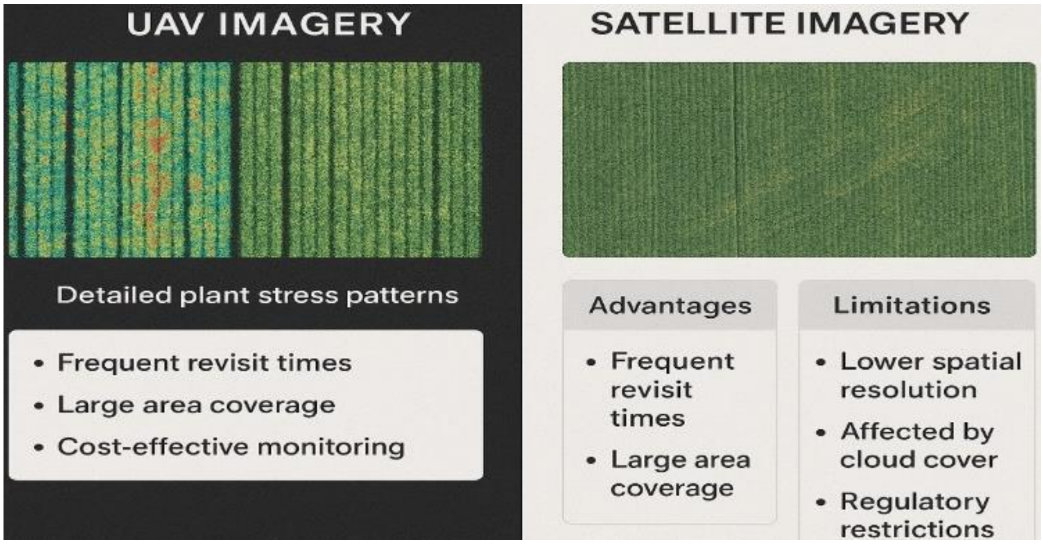

Fig. 1: Comparative analysis of UAV and satellite imagery characteristics for farm-scale monitoring.

The UAV imagery also combined with the satellite data in Malaysia in order to match the area of oil palm plantations and check whether the trees are healthy and manage the plantations (Sabtu et al., 2018). These applications explain how flexible the UAVs are to augment disease surveillance and provision of accurate interventions. UAV-based remote sensing has also been combined with deep-learning systems, e.g., convolutional neural networks (CNNs), to develop high-accuracy crop disease detection models, including under difficult field conditions (Zhu et al., 2024).

GIS in Plant Disease Mapping and Monitoring

The Geographic Information Systems (GIS) is involved in the central stage of plant disease surveillance due to the numerous features that involve spatial visualization, epidemiological modeling, and the decision support. GIS may overlay multiple data sets like distribution of crops, soil properties, climatic factors and diseases in generated layered maps where the patterns, trends and areas of risk are visible. Such geospatial intelligence, empowers various researchers, agronomists and policy makers, to make informed decisions, and take up a particular course of action.

Disease Distribution Mapping

The spatial distribution mapping of plant diseases would be required to map the distribution of the disease within the area, its propagation and the priority control measure. With GIS systems, the user has an opportunity to carry out a combination of RS-based vegetation indices and the environmental data in order to present areas during which diseases occur in their most vigorous form. Taking some examples, NDVI maps between the layers of temperature and humidity can be used to denote stressed areas due to fungal or bacterial infections. GIS-based precision farming through the support of NDVI, thermal picture assistance has assisted to render highly useful areas of drought-stress and disease in sugar cane, thus demonstrating the true value of integrating indices in specific crop surveillance (BeamData, 2025). Google Earth Engine has the potential to contribute to potato late blight monitoring at a large scale because it allows a multi-source time-series-based analysis, which can support dynamic risk assessment and appropriate in-time fungicide application (Chi et al., 2025).

Mobile devices such as GPS can supplement the field data collection process since the crews will be able to tag the infected plants using geotags. These georeferenced observations are added on GIS databases where they can be utilized along with satellite imagery and previous outbreak cases. One of the examples is Ghana, where there were areas where tomatoes grew and were exposed to late blight, which could be forecasted with the help of GIS to monitor the outcome weekly and make necessary changes concerning pesticides (Skelsey et al., 2016). GIS was used to manage the oil palm plantation in Malaysia, as the imagery that has been captured by the UAV was merged with the spatial data related to the health and growth indexes of trees (Sabtu et al., 2018). In paddy field settings, both multispectral and thermal remote sensing data have proven useful to measure the spreading of a disease over different stages of paddy growth, thus enabling focused treatment at a biologically critical stage (Safari & Malian, 2025).

Buffer zones form the other useful GIS tool. GIS is able to identify the potential regions of risk communities because it creates an area around the identified points of disease transmission areas such as producing a map of 2.5 kilometers circling the mosquito larva breeding grounds (Palaniyandi, 2012).

Risk Modeling and Spatial Epidemiology

Spatial epidemiology: Spatial epidemiology is the research of how diseases are distributed in space along with the causes that lead to diseases. GIS has made this a relatively easy job as it brings together weather conditions (e.g. rainfall and temperature), soils conditions (e.g. PH-level, moisture) and crop-specifics such as susceptibility and planting configuration. The analysis of interspecific data is conducted with geostatistical applications, and the risk of the disease is extrapolated between the landscapes through the kriging and inverse distance weighting (IDW), spatial autocorrelation and others.

GIS environments can be used to develop the predictive models to predict outbreak of diseases using the historical trends as well as in the real time scenario. To give one example, in Brazil, GIS assisted farmers to model risks of nematode infestation to ensure that they do not plant in a high-risk region (Sabtu et al., 2018). Decision support systems in India constructed using GIS contributed to the choice of crops carried out in terms of geographic evaluations of risk and they also built the nation to be less lost and more resilient.

One can also utilize GIS in the ecological modeling of the vector-borne diseases. GIS may also predict the number of disease vectors such as mosquito population using the realization of NDVI, land surface temperature (LST) and distance to water body with an aim of determining the places of disease transmission (Palaniyandi, 2012). Satellite imagery has been found to be the most valuable in sub-Saharan Africa where malaria and other diseases, that are transmitted by the vectors, have been followed using satellite imagery by matching the NDVI and LST data with the breeding sites hence offering a scalable intervention in resource constrained areas (Ajayi et al., 2024).

Decision Support Systems (DSS)

All the mentioned DSS Decision Support Systems are itchrroitmy influenced actionable platforms developed by GIS, which assists in controlling a disease. The systems combine the direction of interventional with spatial abidance, acquire guidelines, machine-learning and even the subsequent doge feeds. Based on risk maps of the disease, DSS platforms are also available to present suggestions on such aspects as using fungicide, modifying watering regimes, rotations and other methods of managing land.

In paddy cultivation, a DSS based on GIS was developed in Malaysia where the web-based system enabling it to be monitored on a real-time basis and made a decision regarding the same was designed, and corresponding spatial data were incorporated (Sabtu et al., 2018). GeoAgriGuard also has dashboards that indicate the status of crop health and danger and advisory measures to be taken, enabling the farmers and agronomists to take action rather than respond (Sharada et al., 2025). The results of empirical studies denote that mapping precision of 95 percent can be accomplished, through the simultaneous use of RGB and multispectral unmanned aerial vehicle (UAV) imagery, along with the most cutting-edge deep-learning algorithms, in the case of the Blueberry scorch virus (Jamali et al., 2024). This kind of precision is useful in targeting mitigation actions on infected orchards.

Mobile applications and cloud-based DSS tools also exist which render them scalable, and user-friendly. The innovations come in most handy at resource-limited situations and prior knowledge can be of immense help altered to alter the level and control of the disease in regard to cost of other additions.

RS and GIS Integration in Plant Pathology

The hybridization of Remote Sensing (RS) and Geographic Information Systems (GIS) as a part of the paradigm shift is introducing a new opportunity in terms of monitoring and management of plant diseases. Unlike RS, which presents real-time information of crop health that is non-invasive; GIS can provide spatial analysis, epidemic modeling and decision support. Together, the technologies offer a vast protocol to set, model and successfully interject disease outbreaks in a specific and posh style (Fig. 2).

METHODS

Image Acquisition

RS platforms can be either satellites, UAVs or drones that image spectral, thermal or radar sensor data on agricultural spaces.

Preprocessing

Radical correction of Crude imagery is done to correct the imagery through geometrical and atmospheric means making it both accurate and repeatable.

Disease detection

Medicamentum analysis: Spectral aberration can be compared with vegetation index (e.g. NDVI, SAVI, NDWI or machine learning algorithms (e.g. signal convolution neural network, RF) to identify a crop stress field.

GIS Mapping

Geo reference types (under identified areas of disease), and export to gis software, allow the disease to be super-imposed by environmental data sources such as soil moisture, temperature and altitude.

Development of Management Zone

GIS based on software enables the creation of zones of management to be able to apply certain treatment like rate actions of fungicides (use rate areas) or irrigation zones.

Through such an integrated approach, one can carry out a dynamic disease surveillance that accelerates the capabilities of the stakeholders to know in real time the health of crops, to project future outbreaks, and manage resources ideally.

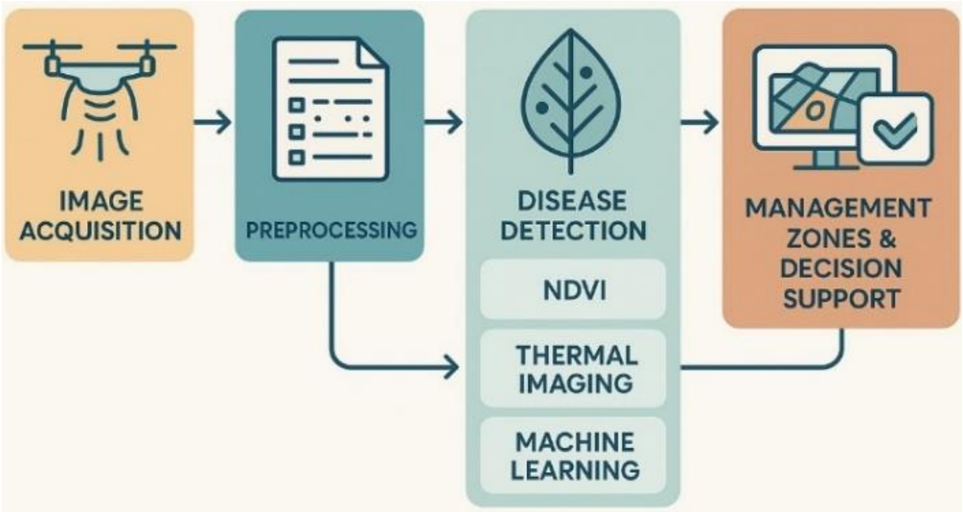

Fig. 2: The integrated RS-GIS workflow for precision agriculture disease management.

Case Studies of RS-GIS Integration

Real world experimenting checks up the effectiveness of the RS-GIS combination assemblage on the use of assemblage to plant pathology in series of practices: Wheat Rust in East Africa: Satellite RS data was also used in this study that identified the outbreak of rust using NDVI and climatic factors with the help of GIS modeling. This enabled timely application of fungicide and reduced the loss in yield (Zhang & Kovacs, 2012). Potato Late Blight In Europe: Signs of the incursion of the disease were identified early using hyperspectral RS-based data whereas GIS was used to map the locations of the development of the disease and the best regions to treat the disease. Not only did this blend increase the number of fungicides work, but it had reduced its effects on the environment (Calderón et al., 2015). Oil Palm Management in Malaysia: Data gathered by Multisensory RS, including VIR, SAR and WorldView-2, were matched and analyzed in GIS to monitor the condition of owner plantations, its growth parameters, and a package of measures that involves renewable planting procedures (Sabtu et al., 2018). GeoAgriGuard platform: It is an RS-GIS based AI channel that operates on UAVs images, deep learning, and spatial analytics to forecast crop stress, pinpoint hotspots of the illness and offer potential decision support to decision-makers in real-time, all in an interactive dashboard (Sharada et al., 2025). These are just some of how RS-GIS integration can be used to aid in monitoring diseases at a small scale (smallholder farm to crop diseases in national agricultural systems) and large scale to crop sustainability.

Recent Advances and Emerging Trends

The role of artificial intelligence (AI), machine learning (ML) and cloud computing as inventions has been particularly high in the sphere of the plant disease monitoring. The recent breakthroughs in artificial-intelligence-based technology, such as federated learning and edge-AI applications are effectively transforming the crops sector by enabling decentralized and privacy-preserving models of detecting the diseases (Sahoo et al., 2024). These new tools are facilitating disease detection that is becoming more accurate, scalable and accessible to more individuals; and are extending the capabilities of Remote Sensing (RS) and Geographic Information Systems (GIS) (Fig. 3).

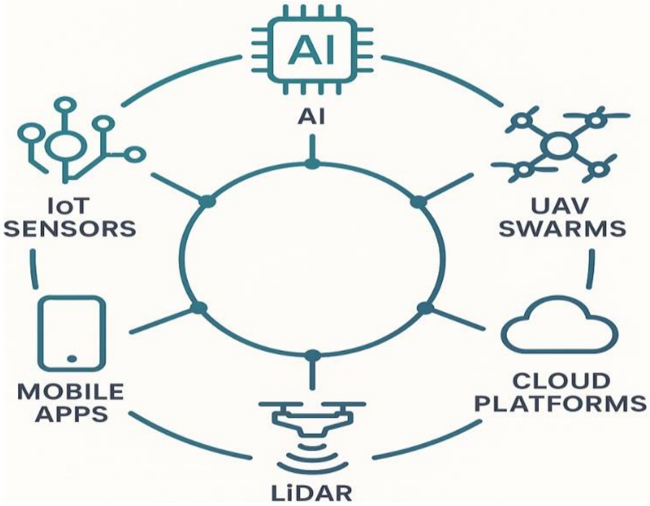

Fig. 3: Emerging technologies driving data acquisition in digital farming.

AI and Machine Learning Integration

Acquisition and interpretation of RS/GE information is also undergoing a change with the assistance of AI/ML. The level of the complexity of the diseases as well as anomaly detection is classified with the help of various deep learning models (Convolutional Neural Networks (CNN), Long Short-term-Memory (LSTM) networks and vision-transformation (ViTs). Recent studies in the layered learning and image-based learning newest research using machine learning specifically in terms of RGB imaging or even hyperspectral imaging has resulted in a significant improvement in categorization effectiveness of crop disease, regardless of illumination or bodily conditions within an area (Dolatabadian et al., 2025). It is these models that the spectral data can be tuned into and taught to gauge the finer folds such that the potential of identifying the disease through automations and with a great degree of precision is achieved.

The first is the GeoAgriGuard which uses the hybrid of the ResNet, Transformer, DenseNet, and AutoEncoders to reveal crop stress and the severity of the diseases. Recently, AI-UAV swarms demonstrated a high rate of accuracy, both in terms of detecting a disease (Brassica crops mainly blackleg and clubroot). Analysis of multispectral and thermal data have shown machine-learning models to reach very high percentages of detection up to 90 and above (Ali et al., 2024). Experience with the YOLOv8-RD model, enhanced with residual fuzzy logic, has also demonstrated excellent resilience in the roofing pine wilt disease, even in circumstances that are typified by noisy imaging or inferior UAV resolution (Yuan et al., 2024). Modern Reviews highlight the history-making capabilities of deep learning in the field of plant pathology, and models like Vision Transformers (ViTs) achieve state-of-the-art results in the domain of disease detection (Wang et al., 2025). The F1-score of accuracy was 96.27 and 97.81 which was better than previous default models and also beat simple CNNs and Support Vector Machines (SVM) as well (Sharada et al., 2025). The dual-branch multiscale model has shown to perform better to identify the yellow dwarf disease of wheat in UAV multispectral imagery with a precision of more than 94 % after being experimentally used (Hao et al., 2025). Similarly, the PlantXViT model is a model based on Vision Transformers, which demonstrated the most adequate adaptation to the field environment; this is why this model may be applied to the real-time monitoring of diseases (Thakur et al., 2022).

Predictive analytics, spatial clustering, and risk modeling AI aids GIS, as well. It is possible to assess previous outbreak-based information, environmental data, and indices acquired through the utilization of RS and calculate the extent of the disease distribution and the location of vulnerable regions based on the algorithms.

IoT and Sensor Networks

Installation of IoT systems on RS and GIS platform is revolutionizing the data collection process in the field. The sensors are installed in the soil, irrigations, and crop canopies to continuously scan the environment in matters concerning the soil moisture, temperature, PH and nutrients. This type of real time measurements is transmitted to cloud based GIS systems and is compared against RS imagery in order to produce dynamic maps of the disease.

Disease surveillance becomes more frequent and stringent with the assistance of IoT to achieve the adaptive management and response of the system within a short span of time. To take an example, soil moisture probes can detect optimal conditions under which fungal growth will take place and ensure intervention mitigation measures are in place to warn and notify.

Cloud-Based Platforms and Mobile Applications

The cloud computing has made it more scalable and accessible to them with the RS and GIS tools. (Sharma et al., 2025) claim to have increased the accuracy of agricultural land mapping by 15%, thereby promoting the causes of precision agriculture by using optimized convolutional neural networks that were trained to use data supplied by Sentinel-2 and Landsat-8 sensors in Google Earth Engine. The user can access the platform such as Google Earth Engine and Microsoft Azure Maps and custom agricultural dashboards, which enables the user to visualize in real-time disease trends, spatial analysis and processing of big data. The attributes of such platforms include teamwork, remote monitoring, and mobile integration-based applications. It has been shown that the use of Sentinel-2 cloud-based imagery and machine-learning tools is an effective framework to detect forest disturbance, with an overall classification accuracy of 90 % to predict canopy turnover associated with pest activity (Molnár & Király, 2024).

Increased use of mobility applications is also coming up where farmers are receiving GIS based information. The possibility of individuals taking the pictures of their damaged plants, having the immediate diagnosis made, and the opportunity to see the map of their location with the risks of a certain disease is offered by such applications like Plantix or PlantDoc. Such resources transform the geospatial intelligence of the resource-constrained environments into a democratic one (Ahmed & Yadav, 2024; Sishodia et al., 2020). The Landsat-8/9 satellites and Sentinel 2 have been valuable in the spatial studies of forest fires with statistical modeling being employed when describing how burns should appear and how they are recovering (Bitek et al., 2025)**.**

UAV Swarms and Edge Computing

The boundaries of real-time monitoring of diseases are being pushed through such emerging technology as edge computing and UAV swarms. Swarms of UAVs could cover large regions within a very short period to offer high resolution information, transmit the information to edge devices to be processed on the fly. The rise of swarm intelligence and AI on edge has allowed multi-drone systems to be combined with autonomous team coordination to the extent that tasks that relate to disease monitoring can be performed without traditional direct control. Real-time processing of data on the edge can decrease latency and enhance efficiencies in the decision-making process in such systems (Sindiramutty, 2025). It decreases the delay and perhaps will allow taking on-site decisions, specifically, when the outbreaks are spread quickly (Lindell et al., 2023).

Autonomous disease detection can also be made through edge computing. The reason behind this is that it is possible to implement the AI models in drones or field sensors. This form of decentralization is more scalable and resilient, especially the disconnected or even inaccessible ones. UAV swarms have become diverse in terms of agriculture use, starting with disease surveillance/mapping applications, crop-yield estimation/prediction. Nonetheless, as it is stated in the literature, the necessity to achieve interoperability and scalability is more significant, not to mention the need to attain standardized protocols (Kumar et al., 2024).

In addition, LiDAR sensors mounted on UAVs provide detailed three-dimensional models of the canopy and enable the researcher to determine the changes in the structure of the diseased plants and the scale of the disease progression in the development of the disease (Debnath, 2025).

Limitations and Challenges

Though the transformative potential of Remote Sensing (RS) and Geographic Information Systems (GIS) has the capacity to effectively use in monitoring plant diseases, the fact remains that several limitations and challenges are hampering its wide spread introduction and successful use. These impediments exist in the areas of technical, economical, infrastructural and environmental (Fig. 4).

Spatial and Spectral Resolution Hindrance

One of the greatest limitations of RS is resolution of satellite imagery. Though coverage of the satellites is broad the spatial resolution may be poor at field level to detect early-infection. Smaller pest and diseases that may manifest as small spotting on the leaf or attacking a few plants can be overlooked in crude-resolution images. Although the resolution is improved in the case of UAVs and drones, they cannot service a wider area appropriately and perhaps may not be useful in large scale projects without significant logistical presence.

The detection of the disease also has spectral resolution influences. Other sensors may fail to identify specific wavelength needed to detect slight biochemical changes of certain disease-transmitted pathogens. Hyperspectral sensors possess better capacity compared to the standard sensors though they are expensive and their information require complex processing.

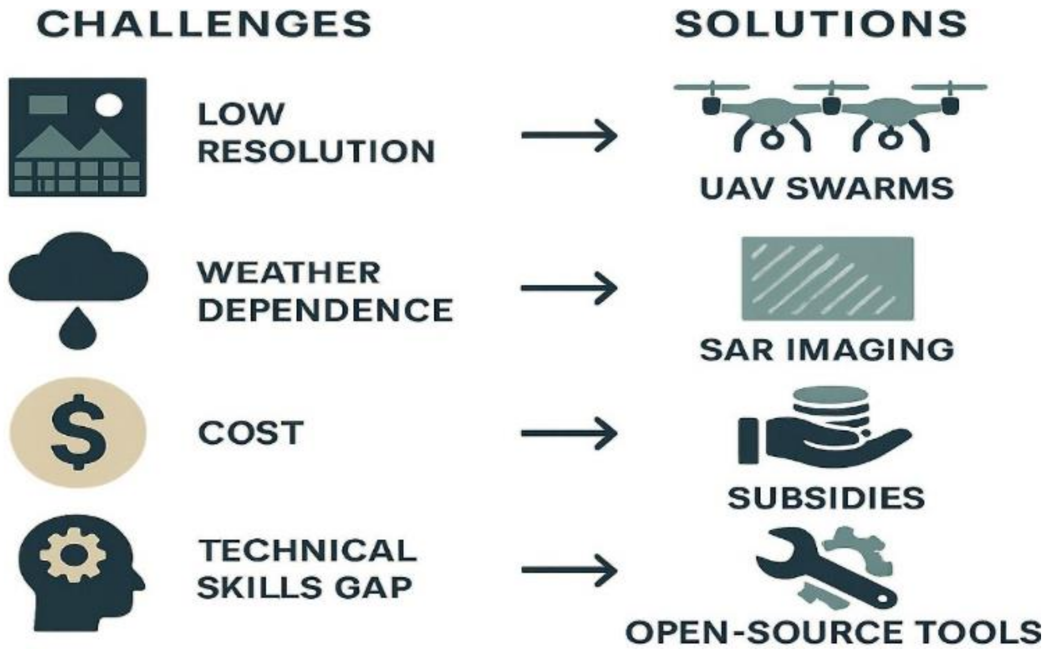

Fig. 4: Framework of challenges and innovative solutions in agricultural remote sensing.

Weather Dependency and Data Availability

The optical RS systems are highly weather reliant. During such significant periods of the emergence of the disease, it is possible to obstruct data with clouds cover, fog, and atmospheric processes. This weakness is put into use to track program consistency and reliability, in particular tropical and monsoon-based regions.

Radar based Synthetic Aperture Radar (SAR) based systems cannot be easily overcome weather related issues however it suffers limited spectral sensitivity and therefore lacks popularity in plant pathology because they are quite costly.

Technical Expertise and Infrastructure Gaps

The safety integrity of UAV swarm networks is seen as a consistently critical issue with the threat of jamming, spoofing as well as data breach that bring the system to a high point of security risks. To this, a set of strong countermeasures aka introduction of strong authentication techniques especially based on blockchain, and deploying encrypted communication protocols have been proposed (Wang et al., 2024). Working with RS-GIS systems needs a special remote sensing or geospatial analysis or data science expertise. Most of the agricultural regions, especially the developing countries, lack skilled human resources, analytical system, and good data. Such loopholes fail to help in advanced disease monitoring programs in smallholder farms.

Also, radiometric correction, georeferencing, and atmospheric correction are complex operations required in RS data preprocessing to be included in GIS. One can read results or apply them to the mode without training and support.

Economic Barriers

Acquisition and the maintenance of RS-GIS technologies may prove too costly to the small-scale farmer. The expenses will be delegated to the purchase of UAVs, sensors, share in software license and cloud storage as well as costs to hire skilled techniciansFinances pose one of the highest adoption barriers but it can be curbed with the assistance of open-source platforms and government subsidy.

Data Integration and Standardization

Information gathered by different sources must be standardized in order to be merged or even linked with others such as information gathered by satellites and UAVs, among other things like IoT sensors as well as field survey data. Data structures are not compatible, software isn incompatible and does not interoperate with the rest, it can lead to errors, business delay and information misinterpretation. In order to make the RS-GIS systems more useful, there is a necessity to establish convergent data integration processes. A promising development technique in energy-efficient UAV coplanar use is the Crow Search Algorithm (CSA), which shows an energy decrease of up to 25 %, during large-scale aerial surveys and does not compromise a high level of accuracy in data-collection (Amutha et al., 2025).

Future Prospects

Monitoring of plant diseases is expected to shipped in the future that applies advanced development and integrating geospatial technology with artificial intelligence and climate modelling and mobile systems. With added stresses such as the problem of climate change, escalating population and resource exhaustion in the agricultural sector, development of resilient data optimal farm systems will depend heavily on Remote Sensing (RS) and Geographic Information Systems (GIS) as the agricultural sector turns even more challenging.

High-Resolution UAV Swarms

Among the potential trends, it is possible to highlight the application of autonomously flying swarms of drones to detect the presence of the disease in real time. Application of autonomous UAV swarms, usually paired with artificial intelligence and Internet of Things implementations, is quickly gaining its footing in precision agriculture, thus enabling broad based and dynamic surveillance of plant health under conditions of heterogeneous climatic environments. Recent research indicates the ability to reduce the operational costs by as much as 40 % (Suresh et al., 2025). These drone networks could be used to scan large farmers/agricultural regions simultaneously producing high definition video and transferring the video to processing operations like edge based processing, or more centralized processing nodes. Optimised cooperative unmanned aerial vehicle (UAV) swarm have been recently used to implement real-time localisation of disease hotspots in farmland, and advanced algorithms are used to dynamically adjust the flight patterns to enhance target detection accuracy by 30 % compared to a single unmanned aerial vehicle (Lopez-Cueva et al., 2024). The squadrons of UAVs also reduce the time of surveillance, expand the spatial boundaries of surveillance, and render the answers to the newly arising disease threats on time (Lindell et al., 2023).

AI-Driven GIS Forecasting

With AI and the model of GIS, one will be able to automate the prediction of the disease based on previous trends and present environment conditions alongside some hypotheses of future climate. Machine learning algorithms facilitate continual learning with new information, are able to make assessments of risk more precise and enables adaptive management efforts. The dynamic decision-making will be encouraged by the AI GIS systems, as the farmers will be capable of anticipating the outbreaks in sequence and protecting themselves way before the symptoms appear (Sharada et al., 2025).

Climate and Pest Model Integration

The RS-GIS of the next generation will incorporate the climate models, pest forecasting models and disease complex models so that the dynamics of diseases can be projected given various antecedent conditions. Such developed integrated models will allow the stakeholders to monitor the impact of temperature, rainfall, humidity, and patterns of the wind patterns, which enhance directions of pathogen movements and the behavior patterns of vectors. This knowledge is critical when using in the long-term planning, especially in those regions facing negative changes in disease ecology due to the climatic change (Palaniyandi, 2012).

Mobile and GNSS-Enabled Platforms

To enhance tracking and the amount of data at field level, mobile-based GNSS (Global Navigation Satellite System) implemented applications will be employed in the increased geotagging. Farmers would then be in a position to use geo-referencing in taking photos of the ill plants and uploading them into cloud based GIS solutions to receive instant diagnosis and treatment recommendations. Such equipment will help every person access geospatial intelligence and seal the digital gap within the rural community (Sabtu et al., 2018).

Real-Time Alert Systems and Edge Computing

Applications that will be integrated through mobile-based GNSS (Global Navigation Satellite System) will be employed to enhance geotagging and information collected at the field levels. Farmers could capture the photos of the compromised crops using geo-located cameras, upload to cloud-based GIS servers and obtain immediate diagnosis and remedial recommendations. They will equip the geospatial intelligence to reach all individuals, eliminating the digital gap in the rural community (Sabtu et al., 2018).

Policy and Capacity Building

To carry out these opportunities, there is need to fund on infrastructure, education and policy based support. The research institutions, governments and even the interested parties that have a financially vested interest should collaborate to establish an open-access program, subsidize assimilation of the technology, build domestic experience. Capacity building Appropriate actions toward making farmers, extension workers, and agronomists aware of geospatial technologies and data-driven decision-making process, should be undertaken.

Conclusion

The application of Remote Sensing (RS) and Geographic Information Systems (GIS) has revolutionized the way plant diseases can be treated via proactive management of better stress forecasting, localization of out-breaks based on spatial mapping and risk modelling. Using combinations of spectral, thermal, and radar data with environmental variables, these technologies offers scalable, multi-dimensional (spatiotemporal) views of plant health that provide plant-scale classification of plant health. Their combinations are applicable in a number of applications such as identification of hotspots of diseases, disease severity estimates, optimization of fungicide treatment, and distribution of resources. These are effective towards diseases like wheat rust, rice blast and citrus greening whose case studies in various parts of the world include the use of platforms like GeoAgriGuard which use UAV image data and AI/GIS dashboard to help in making real-time decisions.

These recent developments in fields of AI, IoT and cloud computing are also being used to create RS-GIS systems as deep learning has improved the rates of classification, sensor networks allow them to acquire monitoring on a real-time basis, and mobile apps have made the geospatial intelligence more democratic to more users. However, barriers such as its low spatial resolution, being highly dependent on atmospheric conditions, and the absence of technical expertise as well as considering the fact that it is rather costly limits its wide-spread usage at least in developing nations where special investments in the infrastructure and skill training of the personnel are required. To know that such tools can be accessed in a level playing field and to benefit the most of them, it is crucial to correct such shortcomings.

Combined with climate modeling, pest prediction and edge computing, in the future RS and GIS will enable dynamic automated surveillance systems. Agricultural resilience will be enhanced with such innovations like high-resolution UAV swarms, GIS platforms on AI, and mobile devices with GNSS that farmers will get and use to take appropriate actions at the right moment to reduce threats. Lastly, RS and GIS are the game-changers in the domain of sustainable agriculture, and the additional evolution of technology will be instrumental in maintaining the health of crops, guaranteeing food sustainability on the global scale, and introducing precision growing in the environment of a progressively diverse environment.

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Data Availability: The data collected for this article are included in the article.

Ethics Statement: No prior study was conducted on live animals/humans; thus, it did not require any ethical approval.

Authors' Contribution: LA designed the study and structured the manuscript outline, contributed to the characterization of materials, performed the analytical data evaluation, contributed to critical writing and manuscript revision and approved the final version of the manuscript.

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