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Geographic information systems and remote sensing: Innovative tools for plant health

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Abstract Agriculture research has a strong emphasis on biotic and abiotic stresses because of the significant economic losses to cash crops. Since plant stress has an impact on crop quality and yield, every effort must be made to identify and treat the problem of plant stress. Geographic Information Systems (GIS) and remote sensing are a new innovative alternative to the conventional diagnosis, detection and management of diseases by - spectral symptoms. The production of crops, including crop protection, can benefit greatly from this contemporary technology. Utilizing data from GIS and remote sensing, disease-affected plants may be identified by the variation in their reflectance spectra when compared to healthy plants. GIS has been widely utilized as a significant instrument for epidemiological research. Remote sensing is a rapid and effective technology that may gather information on the spectral characteristics of earth surfaces from a variety of locations, including satellites and other platforms. The most recent studies are based on the information from spectral. multispectral, and hyperspectral sensors that measure reflectance, fluorescence, and radiation emission, or from electronic noses that detect volatile organic compounds released from plants or pathogens. These sensors may also have the ability to characterize the health status of crops. Agriculture will become more sustainable and safer using GIS and remote sensing technologies, which will also considerably aid to greatly specialize diagnostic and management outcomes. These technologies will eventually become a key piece of a farmer's precision equipment mix, working in tandem with advancements in digitalization and artificial intelligence for precision application across pathogens and crop management demands.

Keywords: GIS, Remote sensing, Plant disease detection, Crop management

Introduction

According to Larcher (1995), plant stress is defined as a significant departure from the ideal circumstances for plant growth that may have adverse effects when the limit of the plant's capacity to adapt is reached. Regardless the crop age, almost every component of a plant can gets stressed. Biological stress causes harm via a variety of plant physiology is heavily influenced by pest, which

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in turn causes usual symptoms emerged as a result. Plants may respond to stress from pests and diseases in a multitude of ways, such as wilting, chlorosis, or photosynthetic necrosis of the leaves reduced leaf size, stunted development, or in certain circumstances, plant components. Numerous alien species, including fungi, bacteria, viruses, nematodes, weeds and phytoplasmas, have a negative impact on crop production globally. These species spread unhindered over great distances via people, goods, and planting materials. There is a need to more effectively control the production of agricultural commodities since there is a global shortage of agricultural products. The loss of crop yields caused by agricultural pathogens causes an imbalance between the production of agriculture worldwide and the demand for food by the world's population. Plant disease epidemiology gives us some knowledge on the spread of diseases in various areas with diverse climatic conditions and facilitates our work appropriate for managing operations and forecasts concerning the disease's spread to several other places (Haggag *et al.,* 2017; Haggag and Ali 2019; Haggag, 2021). If it is feasible to quickly determine the pest's present state and take action, pest management can be more effective.

Advanced technologies, such as GIS and remote sensing have the potential to improve crop protection and agricultural crop output (Haggag, 2021; Zhou *et al*., 2021; Nikhilraman *et al.,* 2022). This review discusses the use of Geographic Information Systems and remote sensing technologies as innovative tools in plant diseases detection and management.

Geographic Information System (GIS)

Tools from geographic information systems (GIS) have several uses in managing Plant Genetic Resources (PGR). In addition to georeferencing, diversity distribution mapping, and projecting optimal places for future collection of crop plants and endangered taxa, GIS also works in conjunction with passport/herbarium/gene bank databases (Sivaraj *et al.*, 2022).

They have been employed in ecogeographic surveys to identify diversity, organize fieldwork, and gather PGR. They are also helpful in identifying PGR conservation areas, specific species, places with a lot of species, and vegetation types that are not adequately or not at all represented in conservation programs. GIS applications may be used to locate hotspots, the spread of pathogens and viruses, create early warning systems, create risk assessment models, help with site-specific protective measures, in terms of biosecurity (Sivaraj *et al.*, 2022).

The use of the Geographic Information System (GIS) has expanded the scope of diseases control (Haggag *et al.,* 2017; Haggag, 2021). Ample opportunities for pathogens monitoring, identification, and time management in agriculture have been made possible by recent developments in the use of GIS technology. Finding and recording the interactions of physical factors at other places with various species, soil textures, elevation, and land use may be significant for improving diseases management strategies. GIS approaches in diseases control may offer in-depth details on the physical and biological interactions with metapopulation dynamics, as well as information on spatially explicit models to forecast future pest populations by choosing suitable habitat conditions.

Geospatial analysis, mapping, and large-scale data collecting are required to stop the spread of pest diseases. It is used to identify and assess patterns in order to appreciate how the illness interacts spatially with insects, soil, and plants. GIS is used to track monitoring programs including spraying programs, trapping solutions, treatment, and other measures by providing precise location information that helps pest control decisions. Based on the collected data, GIS can aid project risk assessment models for pest management and control. Develop a viable strategy to stop the spread of illness and identify important intervention sites. With the use of digital tools like GIS and Global Positioning Systems (GPS), agricultural lands may be extremely carefully mapped. Production systems for precision agriculture could be created using this technology, soil testing, and yield monitoring.

Through data visualization, data querying, data management, and analysis of risk pathways, GIS has been used for pest monitoring and detection. It can also be useful in identifying places where a pest introduction is most likely to occur. In order to assess the area, change in an alien species' spread and to identify it, prediction models can be created. The application GIS is significant in plant quarantine because it benefits the economy, takes a proactive approach to protecting agriculture, aids in quality control, and serves as a decision-support system (Sivaraj *et al.*, 2022).

Remote sensing

Principle of operation

Remote sensing is defined as the technique of obtaining information about objects through the analysis of data collected by special instruments that are not in physical contact with the investigated object. The definition given by the American Society for Photogrammetry and Remote Sensing (ASPRS); remote sensing is the science, art, and technology of gathering trustworthy information about real world objects and their surroundings without making direct physical touch. Remote sensing technology may be based on the ground, in the air, or through satellite. Satellite remote sensing succeeded in aerial remote sensing in the 1960s. The process of remote sensing began with the sun (passive) or with the satellite itself (active). When radiation strikes the earth's surface, it is absorbed, transmitted, and reflected. These reflected radiations are then picked up by satellite sensors, which then use them to learn about the components that make up the terrestrial environment. These include terrain, vegetation, water bodies, hydrological cycles, and agricultural ecosystems. Different electromagnetic spectrum wavelengths are used to record the reflected radiations. The near infrared (NIR) ranges from 0.7 to 1.3 micrometers, the middle infrared (MIR) ranges from 1.3 to 3 micrometers, the thermal infrared (TIR) ranges from 3.0 to 14 micrometers, and the microwave ranges from 1 mm to 1 micrometer are all recorded. It simply referred to the collection of information about an object without coming into contact. Also, it can define as an image of the scene being seen often represents the output of remote sensing equipment. It is a quick, non-intrusive, and effective method for gathering and analyzing the spectral characteristics of earth surfaces from a variety of distances, from satellites to ground-based platforms. Technology for remote sensing is helpful for calculating and logging electromagnetic radiation emissions from the target region and the sensor equipment. Cameras, radar systems, electromagnetic scanners, and video cameras are some of the several sensor instruments employed in this technology. Its operation is reliant on electromagnetic energy and the interaction between radiation and earthen targets.

Remote sensing and crop health

For field crops, horticulture, plant breeding, and the enhancement of fungicide efficacy, it is crucial to accurately predict plant disease prevalence and severity as well as the detrimental effects of plant infections on agricultural products. The most frequent procedures for identifying and diagnosing plant diseases include visual examination of recognizable symptoms, microscopic analysis of morphological characteristics, as well as molecular, serological, and other microbiological methods. These techniques are employed in both illness diagnosis and academic studies. The identification and measurement of plant pathogens and illnesses have undergone revolutionary change in recent decades as a result of the development of molecular and serological approaches. In order to assess management strategies for the diseases, estimate pathogen variation and evolution of new races, choose sources of resistance, and resolve the components of complex diseases caused by two or more pathogens and interactions between them as well as relationships between the plants and pathogen insight into the pH, it is necessary to quantify the pathogen inoculums (Nagasubramanian *et al*., 2018).

To overcome host defenses and adapt to pathogen onslaught, pathogens in nature are continually altering and evolving new pathogenicity (Nagasubramanian *et al*., 2018).

The use of remote sensing technologies to manage pathogens assaults and crop stress has become increasingly effective. One of the main advantages of employing remote sensing is that it offers a thorough, precise, and timely forecast of pest assaults and crop stressors, which may optimize pest control, decrease crop loss, and lower cultivation costs (Roy *et al.,* 2023). In addition to pest control, remote sensing may identify agricultural challenges such nutrient or water shortages, pathogens infestations, and disease development. A crucial part of integrated pest control tactics, remote sensing techniques can increase spatial and temporal resolution (Roy *et al.,* 2023). It is necessary to adopt and incorporate novel strategies and rating systems in order to acquire an objective and trustworthy automated diagnosis and detection of plant diseases. It aids in calculating the disease's severity.

The choice of whether or not to use a fungicide to manage a sensitive pathogen depends on both the presence of a symptom and if the severity of the diseases exceeds the action threshold level determined from economic considerations (Satapathy, 2020).

Monocyclic infections (such smut fungus) do not require management when symptoms initially present since the damage has already been done. In contrast, polycyclic pathogens rarely cause the onset of early disease symptoms, and if effective fungicides are available, it may be possible to control the expected increase in disease severity from the pathogen's future generations to keep the severity of the disease from rising above the economic threshold level.

Remote sensing can help protect plants from possible assaults by pests, fungus, or bacteria in addition to helping identify plants that are stressed due to a lack of nutrients or water. It is feasible to have early warning and stop a pest or disease from harming the crops by taking suitable action at an early stage by integrating agricultural expertise with remotely sensed data. Diseases can reduce chlorophyll and photosynthesis. Area Index (LAI) of a group of plants, alerting farmers to take the necessary precautions. In order to reduce the amount of chemicals needed in a crop management regime, remote sensing can help identify the plants that need fertilizer or pesticides the most. Bawden (1933) and Colwell (1956) were the first to utilize visible aerial photography to identify viral infections in tobacco and potato crops.

Vegetation differs from other land surfaces because it tends to absorb strongly the red wavelengths of sunlight and reflect in the near-infrared wavelengths. Chlorophyll absorbs light in the red channel (0.58-0.68 microns) and foliage reflects light in the near infrared channel (0.72-1.10 microns). Therefore, higher photosynthetic activity will result in lower reflectance in the red channel and higher reflectance in the near infrared channel. This signature is unique to green plants. Dense vegetation shows up very strongly in the imagery, and areas with little or no vegetation are also clearly identified. Spatial and temporal variations in vegetation indices have been found to be linked to prevailing climate, ecosystem, terrain and soil properties.

The NDVI is one of the most common indicators of crop growth characteristics and, indirectly, of specific site qualities (Sumfleth and Duttmann, 2008). A serious problem in partly vegetated areas is the influence of soil background reflectance on NDVI, which produces decreasing NDVI values with increasing soil brightness under otherwise identical conditions. Therefore, several variations on the NDVI have been developed, e.g. The Soil Adjusted Vegetation Index (SAVI), the Transformed SAVI (TSAVI), and the Global Environment Monitoring Index. NDVI is calculated from the red and near-infrared reflectance (rRed and rNIR) as:

$$\mathbf{NDVI = (rNIR - rRed) / (rNIR + rRed)}$$

The obtained NDVI values are located in the range (-1 to 1), negative values point to non-vegetated surfaces, while positive values indicate vegetated surfaces. NDVI values more than 0.5 indicating dense vegetation, while values less than 0.0 indicating no vegetation (Figure 1). Several soil properties have been related to mono-temporal NDVI in local scale studies are root zone soil moisture, soil color, soil texture and water-holding capacity and soil carbon and nitrogen content. Alternatively, NDVI time series have been used to derive soil patterns by analyzing changing NDVI values during a growing season and the onset of senescence during a dry season. Hansen *et al.* (2009) found larger changes in vegetation greenness on steeply sloping valley sides with sandy soils than in nearly flat, waterlogged valley bottoms.

Although utilizing infrared imaging to distinguish between disease-related alterations that occur in the interior leaf structure of cereal crops. Site-specific disease control has benefited from the recent application of spectrum sensors (Table 1). Hyperspectral technology, for instance, was used to explore the identification and quantification of yellow rust in wheat crops (Kuska *et al*., 2015). Two measurement platforms are used in field tests with the hyperspectral camera: [1] a ground-based vehicle and [2] unmanned aerial vehicle. These sensors particularly use – the electromagnetic spectrum between 400 and 2500 nm, to monitor crop canopy and measure light reflected during pathogen infection and disease progression in severity of yellow rust in wheat field. For the monitoring of crop plant diseases and the evaluation of their effects on production, high spatial resolution satellite devices and airborne imaging have been utilized (Rani and Jyothi, 2017; Zheng *et al*., 2018).

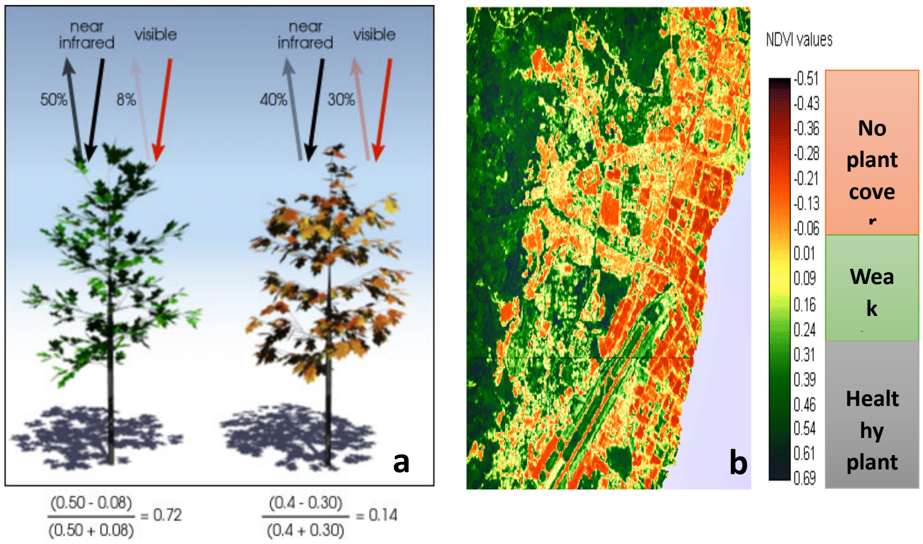


Figure 1. Normalized difference vegetation index (NDVI) reflects the photosynthetic activity (a), variation of NDVI over a cultivated area reflect the plant status (b) Available at: http://www.geoscience-environment.com

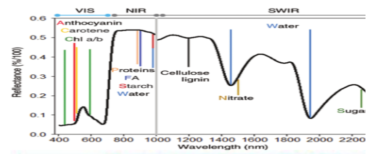
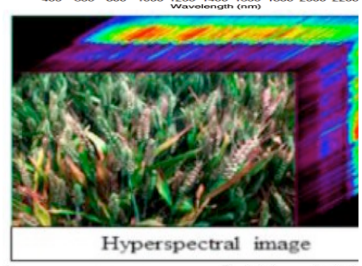
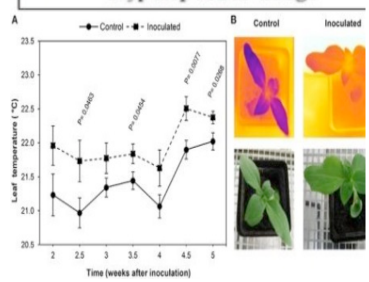
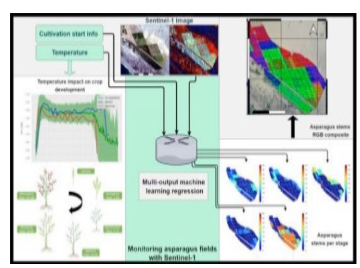
As shown in Figure 2 and Table 2, optical sensors have great promise for noninvasive diseases diagnosis and detection (Oerke *et al*. 2014). Imaging and noninvasive sensors that can aid in diagnostics and plant disease detection are becoming more widely available. Precision agriculture and plant phenotyping provide new prospects thanks to advancements in sensor and information technology, as well as the growth of GIS.

The two categories of remote sensing techniques listed below are based on sensors and are used to detect plant diseases:

1. Imaging strategies
   - RGB camera
   - Multispectral imaging
   - Hyperspectral imaging
   - Thermal photography
   - Imaging using fluorescence
2. Methods other than imaging
   - Spectroscopy using the VIS and IR
   - Fluorescence spectroscopy
   -

Plant diseases can also be found using other imaging methods, such as Terahetz spectroscopy and X-ray imaging, however none of these methods are economical. The numerous optical sensors used in plant disease detection were evaluated by Mahlein (2016) as illustrated in (Table 1).

Table 1. Commonly utilized remote sensing systems for plant disease diagnosis and monitoring

Remote sensing systems	**Main characteristics**	**Merits and Demerits**	**Application capability**	**Pictorial representation**
VIS-SWIR	Find out destruction caused by plant diseases & pest infestation by emittance in VIS-SWIR region.	Steady, provide authenticated monitoring results, but poor performance on early detection.	High[relative instruments & algorithms are available at relatively low price]	 
Fluorescence and thermal	Records pre symptom physiological changes	Possess a capability to provide presymptom detection. But currently tough to apply in large area.	Medium[Lot of systems are available currently for research, which ar high cost with low applicability]	
SAR & Lidar	Records structural changes caused by disease and pests	Capable to indicate changes in plant morphology. The systems and case studies are presently lacking.	Low[Predominantly remain at conceptual stage]	

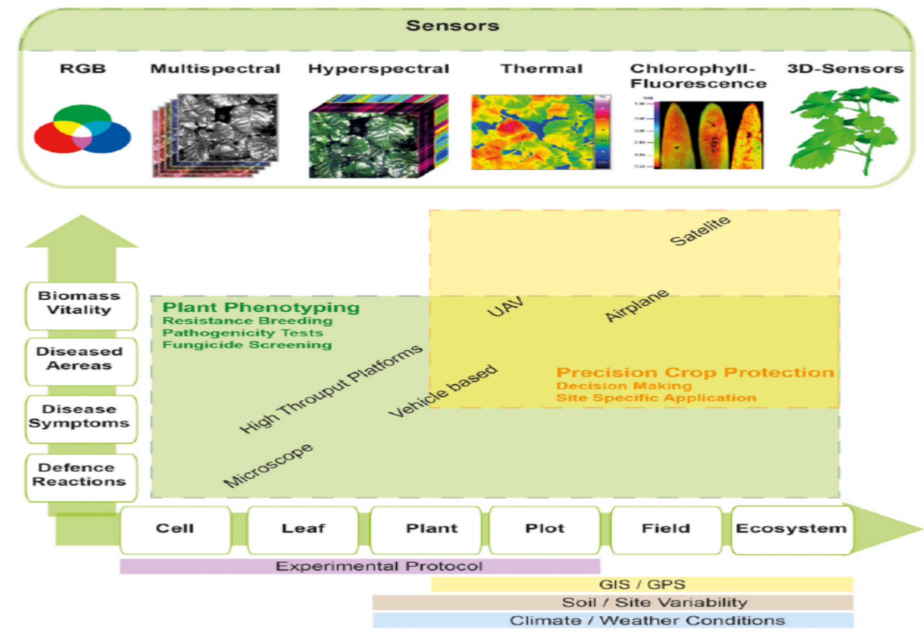


Figure 2. Overview of the existing sensor technologies for plant disease detection and attribution, modified after Oerke *et al*. (2014)

Different applications

Applications of remote sensing for effective plant protection crop protection against plant diseases is important. In response to this worry, modern challenges sprung up with logical arguments. Progressively more viable natural and unneighborly arrangements are needed. For the purpose of making a decision on a later management practice, the precise diagnosis of the initial infection and illness dynamics is crucial. Plant disease sensors may be employed once for quality control (by the food industry or quarantine authorities, for example) or they may be linked into autonomous systems for the continuous monitoring of crops for plant diseases, which entails checking and maintaining a continuous record of the crop health status (Nikhilraman *et al.,* 2022). Several examples are summarized in Table 2 from the much more recent advancement in various pathosystems utilizing various kinds of very sensitive sensors and numerous data analysis pipelines that have been published. The several sensor systems described are covered in-depth evaluations (Neumann *et al.,* 2014; Mahlein, 2016).

Table 2. Examples of research on plant diseases detection by various optical sensors (Mahlein, 2016)

Sensor	Crop	Disease/Pathogen	Reference
RGB	Cotton	Bacterial angular (*Xanthomonas campestris*) Ascochyta blight (*Ascochyta gossypii*)	Camargo and Smith (2009)
	Sugar beet	Cercospora leaf spot (*Cercospora beticola*), Sugarbeet rust (*Uromyces betae*)	Neumann *et al.* (2014)
	Grapefruit	Citrus canker (*X. axonopodis*)	Bock *et al*. (2008)
Spectral sensors	Barley	Net blotch (*Pyrenophora teres*), Brown rust (*Puccinia hordei*),	Kuska *et al*. (2015)
	Wheat	Head blight (*Fusarium graminearum*), Yellow rust (*Puccinia striiformis* f. sp. *tritici*)	Bravo *et al*. (2003), Moshou *et al*. (2004)
	Sugarbeet	Cercospora leaf spot (*C. beticola*), Sugarbeet rust (*U. betae*)	Mahlein *et al.* (2010, 2012) Bergstrasser *et al*. (2015)
	Tomato	Late blight (*Phytophthora infestans*)	Wang *et al*. (2008)
Thermal sensors	Sugarbeet	Cercospora leaf spot (*C. beticola*)	Chaerle *et al.* (2007)
	Cucumber	Downy mildew (*Pseudoperonospora cubensis*)	Oerke *et al*. (2006), Berdugo *et al*. (2014)
Fluorescence imaging	Wheat	Leaf rust (*Puccinia triticina*), Powdery mildew (*Blumeria graminis* f.sp. *tritici*)	Burling *et al*. (2011)
Sugarbeet		Cercospora leaf spot (*C. beticola*)	Chaerle *et al.* (2007); Konanz *et al.* (2014)

Multi-spectral remote sensing for the identification of multi-temporal wheat diseases High resolution Quick Bird satellite multispectral multi-temporal images was examined by Franke and Menz (2007) for the purpose of locating powdery mildew and leaf rust on wheat in Bonn, Germany. The first scene had a classification accuracy of 56.8%, but the subsequent scenes had accuracies of 65.9% and 88.6%, respectively (Franke and Menz, 2007).

Aerial photography was first employed to determine cereal Robert Colwell, University of California, for studying aerial photography in-depth for the first-time observation of yellow dwarf, oat, and wheat black stem rust oat and published his work in the magazine Hilgardia in (Colwell, 1956). Irradiation, color, and panchromatic This study made use of films (Aerial Ektachrome).

Ju *et al*. (2023) used an unmanned aerial vehicle to collect multispectral imagery of the wheat canopy, built a wheat leaf rust monitoring model using the backpropagation neural network (BPNN) technique. These models provided a theoretical foundation and technological assistance for evaluating plant illnesses and screening disease-resistant wheat cultivars while properly tracking leaf rust in winter wheat.

The use of Airborne Data Acquiring and Registration (ADAR) for the diagnosis of rice sheath blight rice detection and monitoring system: Qin and Zhang (2005) sheath blight disease in central Arkansas, USA, employing four. The ADAR collected aerial remote sensing photos (Airborne Data Acquiring and

Registration) System 5500. The four bands on the photographs were as follows: blue: band 1 (450–540 nm), green: band 2 (530–600 nm).

Hyperspectral remote sensing of plant disease

Hyperspectral imaging has attracted a lot of attention in agriculture recently. By using narrowband sensors, this technique improves the information's quantity and quality. The data is based on a spectral Z-axis, spatial X and Y axes, and coordinate systems. Winter wheat with yellow rust disease (*Puccinia striiformis*) was subjected to VNIR hyperspectral imaging by Bravo *et al*. in 2003. They grouped the collected data into 19 wavebands, each measuring 23 nm in width and spanning the whole spectral range between 463 and 895 nm. According to their findings, sick plants had increased reflectance in the VIS region due to decreased chlorophyll activity and higher absorption in the NIR area mostly as a result of internal leaf structure degradation (Bravo *et al*., 2003).

Hyperspectral imaging data can offer more information than non-imaging spectral technologies, such as shape, gradient, color, etc. With a wavelength variation, hyperspectral imaging technology has a high resolution of picture data (Xing, *et al.,* 2019). A nanometer is the resolution level of the spectrum in the visible to shortwave infrared region. Numerous spectral bands possibly hundreds of them could exist. There are continuous spectral bands, and each may yield a full hyperspectral resolution spectral curve. Location of each picture pixel, the hyperspectral data frame is therefore created as a picture cube in three dimensions, as seen in Figure (3).

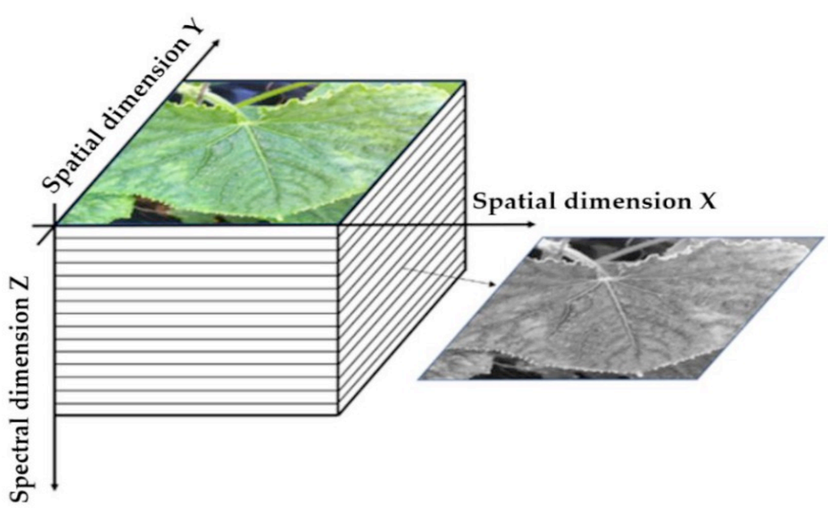


Figure 3. Structure of a cucumber leaf's using hyperspectral image data cube

Utilization of hyperspectral data for the illness potato late blight

The benefits of hyperspectral mapping unity, which can precisely monitor crop development and illnesses, are fully used by the implementation of hyperspectral imaging technology in agriculture (Wang *et al*., 2022). Hyperspectral data was used by Ray *et al*. (2011) to analyses potato late blight in Amritsar, Punjab. There were 512 channel spectroradiometer between 325 and 1075 nm. Spectra showing average reflectance of a variety of disease infection levels are present in the potato crop (Figure 1). According to the hyperspectral reflectance curves, because robust plants reflect light well Region NIR (beyond Low red reflectance (about 650 nm) and reflectivity around 750 nm. Vegetation indicators, namely the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) Ratio (SR) and Red Edge Indexes – were computed via reflecting qualities. The variations in the vegetation indices for plants with various disease infestation levels were discovered to be quite important. The ideal hyperspectral imaging wavebands to distinguish between healthy and diseased plants were 540, 610, 620, 700, 710, 730, and 780, but up to 25% infection may occur at 1040 nm, reflectance at 710, 720, and 750 nm was used for separating infected plants (Ray *et al.*, 2011).

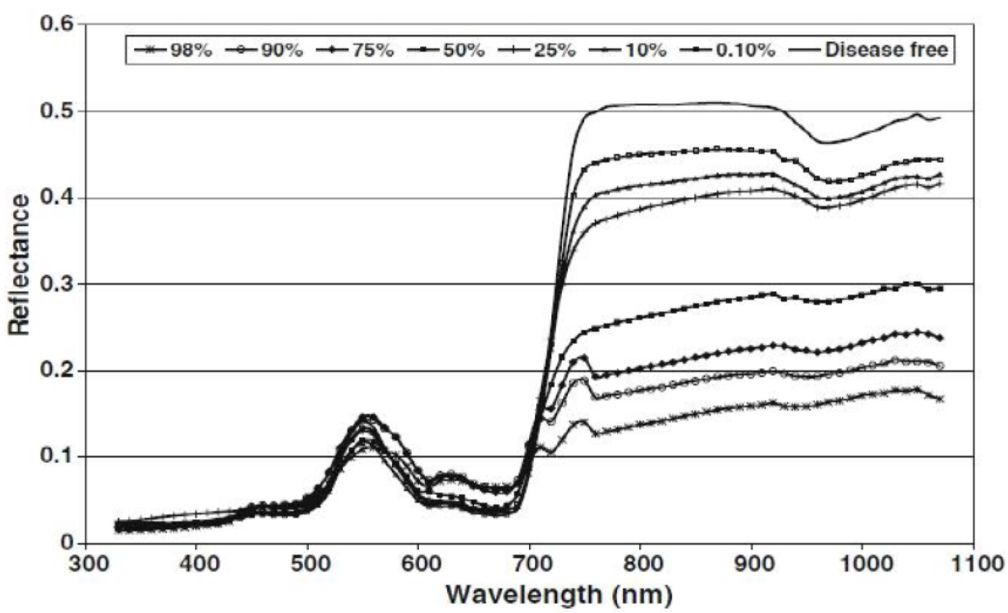


Figure 4. Reflecting of potato crops at different level of late blight infestation (Ray *et al.,* 2011)

Hyperspectral imaging data can reveal stressors brought on by abiotic environmental variables, crop growth, and biological harm in addition to infections. The most recent machine learning models should be combined with hyperspectral data processing techniques for plant disease diagnosis, and fresh methods should be presented to handle challenging environmental circumstances. Therefore, further biotic or abiotic stress effects on plant spectrum traits may be eliminated from models used to identify plant diseases. As a consequence, field practice could benefit more from this technology (Wang *et al*., 2022).

Future perspective

Plant diseases have a key role in post-harvest yield decreases and huge economic losses in agriculture production around the world, especially in light of recent climate change. Many effective methods for identifying, monitoring, and assessing plant diseases have been developed. Future research should also focus on improving pathogen logical analysis, biochemical analysis, and expert interpretation of the visual components. Nowadays, interest in hyperspectral technology, a non-invasive technique, is growing. As a result, it is important to emphasize integration analysis of satellite scales while also researching issues and new developments in hyperspectral technologies for plant identification. The use of targeted hyperspectral satellite missions results in the gathering, pre-processing, and analysis of enormous amounts of data, allowing for the real-time dynamic monitoring of plant disease at the regional, national, and international levels.

Since new discoveries and advancements are being made to enhance the capabilities of the technology, the application of GIS and remote sensing in agriculture promises to have a promising future. It is expected that remote sensing would keep making a substantial contribution to raising crop output and sustainability. One of agriculture's most potential futures is the application of artificial intelligence (AI) and machine learning (ML) technologies to remote sensing. These technologies allow for the automatic processing of remote sensing data and the delivery of real-time information to farmers. Then, farmers may make crucial choices regarding crop management, such as when to plant, water, treat diseases, and harvest crops.

Remote sensing may be a key tool in the agricultural sector, which is also facing a significant challenge from climate change, to monitor and adapt to changing weather patterns. Farmers may utilize remote sensing to find farms that are more susceptible to stress in order to manage their crops more successfully.

It's exciting to work in a field that is expanding quickly and where remote sensing and GIS in agriculture seem to have a promising future.

Conclusion

The production of agricultural products on a large scale necessitates the timely diagnosis of diseases and management. In order to diagnose and spot recurring patterns of plant disease as well as other issues like weed infestations without coming into physical touch with the plant or plant components, GIS and digital imagery are particularly helpful. Strong solutions for disease identification and detection with high accuracy and sensitivity that will enhance plant health management may come from a highly multidisciplinary approach with a direct connection to practical agriculture.

Remote sensing offers a quick, non-intrusive, dependable, precise, and accurate disease assessments that are useful in keeping track of and predicting outbreaks. Multitemporal data from remote sensing offer enormous promise for agricultural the regional mapping of diseases. Based on spectrum using a classification methodology is a useful technique for crop finding the sickness. By looking at all of the environmental characteristics and accessible natural resources as a whole system, remote sensing has emerged as a viable method for integrated pest control.

Agriculture has already benefited greatly from remote sensing, and things only seem to get better from here. Remote sensing is projected to play a more significant role in boosting agricultural yield and sustainability in the years to come with the integration of artificial intelligence (AI) and machine learning (ML) technologies. technologies, precision agriculture, disease and pest detection, climate change adaption, and enhanced data availability. As a result of its integration with other GIS and remote sensing technologies, its capabilities have been further increased, making it a crucial part of integrated pest control methods in the twenty-first century.

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