

Review Article

Recent Advances for Detecting and Addressing Plant Disease: Towards Future Farming

Abstract

Pests and pathogens inflict enormous financial harm on the global farming industry. Monitoring plant health and early pathogen detection is essential for facilitating successful management strategies and preventing the spread of disease. Various traditional methods and serological techniques have been found to be time-consuming and require handling skill. Also, the reliability of the result is uncertain, and it is hard to diagnose the pathogen during asymptomatic stages. Hence, the innovative sensors based on host reactions assessment, phage display-based biosensors, and bio-photonics in combination with other systems, remote sensing techniques integrated with spectroscopy-based approaches allow for high spatialization of data; these techniques could mainly be of immediate benefit for initial identification of infection and early control with limiting the use of Systemic Fungicides and developing a sustainable environment with high yield.

Keywords: Bio-photonics, Bio-sensors, Pathogen, Remote Sensing and Spectroscopy

Introduction

Plant diseases contribute to substantial economic losses to hectares of croplands and postharvest agricultural products. Plant disease epidemiology is controlled by a large number of components, actors and factors. With the advancement of new tools for monitoring and crop modelling techniques, studies of various environmental factors have become comparatively easy. Various computer-based simulation programs have been developed via Artificial intelligence that regularly monitor crop health. Earlier, through aerial photography and imaging techniques, geography and land patterns were recognized for commercial crops during the 1920s to record the severity of cotton root rot, pictures were taken through helicopter imaging techniques.

The disease management in a crop is triggered by various heterogenetic factors such as topographic conditions, soil conditions, neighbouring fields, microenvironment of crop, and sources of pathogen inoculum, which often result in varied disease manifestations. Disease patterns may vary from site to site, year to year, and over time during an epidemic in a particular field. Plant disease epidemics are cyclic and spread repeatedly in relation to the host and environment. The inoculum development consists of fungal spores, bacterial cells, nematodes, viruses, or vectors, which gain entry and establish themselves via host infection. The pathogen selected within the host develops new inoculum, which further disseminates to the susceptible site to initiate new infection. Pathogens that produce only one cycle of infection per crop cycle are called monocyclic pathogens, whereas polycyclic pathogens produce more than one infection cycle per crop cycle. Thus, accordingly, farmers have to extend the visual rating of disease incidence and severity to a nominal number of samples to decide whether there's a requirement of field spray or not.

The heterogeneity of disease spread helps to decide the quantity of fungicide sprayed during the crop growing season, which helps minimize undesirable environmental

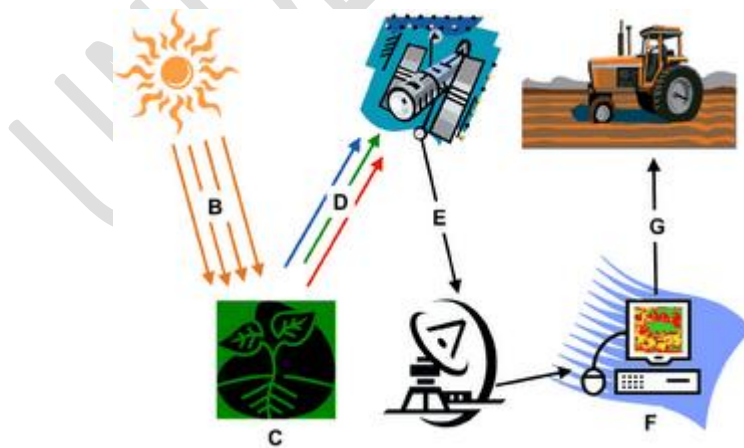
contamination by spraying when required. This will also decrease the selection of fungicide resistance in pathogens and slow down the rate of strain variability in pathogens. Thus, essentially, site-specific monitoring of plants is necessary to determine whether the plant is diseased to what degree and whether there is a requirement of disease control. The fungicide usage was significantly reduced in France without negatively impacting productivity by 47%, with 59% of farm profitability.

The present detection and diagnosis of plant disease currently rely on visual rating of plants. In case of doubt, specialized techniques such as nucleic acid assay, ELISA, qPCR or lab based serological technologies are used. But, these techniques cover only a representative sample and are often time-consuming. The indirect remote sensing methods such as thermography, fluorescence imaging and spectral techniques allow repeated monitoring of the crop of interest. The Gas chromatography and electronic nose (e-nose) techniques require the volatile organic samples or VOCs released by infected plants or the infecting pathogen, which detect the presence of disease in individual fields.

Diseases (caused by fungus, oomycetes, bacteria, and viruses) have been estimated to account for 16 percent and 11 percent of the feasible crop yield. Plants must be protected from diseases and other pests, it is widely agreed. Integrated pest management (IPM) systems combine mechanical, biological, and chemical instruments with other supporting technologies to achieve effective, efficient, and sustainable pest management.

In crops, disease control often assumes a uniform pattern of disease spread; thus, crops are sprayed at uniform application rates. However, crop heterogeneity resulting from changes in soil conditions, topography, adjoining fields, microclimatic conditions, and pathogen inoculum sources frequently leads to a heterogeneous distribution of illnesses displayed as patches, gradients, or random patterns. Remote sensing can be employed as a first step in disease management at a given location and profile plant genotype responses to pathogen assault.

Integrated pest management (IPM) systems combine mechanical, biological, and chemical instruments with other complementary technologies to achieve effective, efficient, and long-term pest management.



(Source: NDSU, 2004)

Fig:1 Plants (C) receive electromagnetic energy (B) from the sun (A). The leaves allow some of the electromagnetic radiation to pass through. The reflected energy (D) is

picked up by the satellite's sensor. After that, the information is sent to the ground station (E). The data is examined (F), and field maps are displayed (G).

Scope

For a prolonged period, crop disease detection and diagnosis were based on human assessment and the operator's specialized knowledge. Various serological techniques, such as DNA-based technologies, are often time-consuming and require significantly improved facilities and skills for plant pathogen diagnosis and management.

Sensors should be unbiased, exact, fast, and available 24 hours a day, seven days a week. Plant disease sensors can be used once for quality control (for example, by the food industry or quarantine authorities) or linked into autonomous systems for constant monitoring of products for plant pathogens, i.e., examining and maintaining a complete record. A systemic assessment of a crop using technical sensors can enable the operator to take action when illnesses are detectable or exceed action threshold levels. Sensors ought to be able to

- A) recognizing a pathogen-caused change in the health state of the crop
- B) determining the disease
- C) determining the disease's severity

The ability to distinguish between potential diagnoses based on disease-specific signs is required for disease diagnosis. For imaging systems, quantifying typical illness symptoms (disease severity) and assessing leaves infected by many pathogens is simple. Still, non-imaging sensors and sensors with insufficient spatial resolution face a problem. In some situations, disease detection is the impression of a variation from a healthy crop/fruit. There is no need to identify or quantify sickness in these situations. To detect plant diseases, the Global Plant Protection Convention's protocols combine phenotype, immunological, and genomic techniques; these methods give complimentary information (Martinelli *al.et.*, 2015). Physical sensors allow for the employment of autonomous systems for quarantine inspections, which can be used as a first step in identifying suspect material that can then be tested and validated using molecular techniques for pathogen detection.

Table1 Disease identification: possible methods, parameters, and users

Scope	Application	Environmental circumstances	User
Monitoring of quarantine	Plant quality and safety inspections	Semi-controlled	Exporters, importers, and regulatory agencies are all involved.
Plant product quality assurance, particularly for post-harvest illnesses		controlled	Food enterprises
Forestry	Crop health monitoring.	Woods, forest plantations	Forest management on both private and public lands
Field Crops		Field	Contractors in the agricultural industry

Speciality crops grown in greenhouse		Semi-controlled	Gardeners
Plant genotype responses phenotyping.	Disease resistance selection in crops	Semi-controlled	Plant breeders

Source-Oerke.*et. at.*,2020

Post-harvest sensing of the safety and quality of (processed) plant products in the food business comprises assessing ripeness, color, and storage compatibility; Detecting flaws, bruising, and diseases in fruits and vegetables, as well as determining mycotoxin contamination from fungus, such as *Aspergillus flavus* in maize kernels (Yao *et. at.*,2013). Sensors and high-throughput platforms thrive in highly regulated environments. The sorting and grading procedures necessitate real-time decision-making based on sensor data. Crop germplasm can be phenotyped under controlled conditions and in field stations for disease susceptibility.

Phenotyping devices need advanced hardware, yet they deliver high throughput and frequently monitor the plants numerous times during the growing cycle without immediate data analysis. Disorder identification is unnecessary while administering the target pathogen vaccine, but disease quantification is essential.

Theoretical foundation and definition

By detecting the electromagnetic radiation reflected/backscattered or emitted by the Earth's surface, Remote sensing is a technique for collecting information on an object without physical touch (Jong and Meer, 2006). In this application, RS is an indirect assessment technique that can monitor vegetation conditions from a distance and determine the spatial breadth and patterns of vegetation attributes and plant health. Sensors classified as active or passive sensors create artificial radiation and detect reflected or backscattered energy, whereas passive sensors monitor reflected solar radiation or emitted thermal radiation (passive sensors). Examples of active remote sensing instruments include Radar and lidar. Various passive instruments used to measure solar radiation in the visible (VIR range (400-700), near-infrared (NIR range 700- 1100 nm) and short infrared (SWIR-1100-2500 nm), and the thermal infrared (TIR-3 to 15 μ m) region are used in remote sensing for plant disease detection.

Variables defining canopy structure, such as leaf area and orientation, spatial arrangement, roughness, and the plant element's optical, dielectric, or thermal properties all impact vegetation's spectral signature (Baret *et. at.*,2007).

Also, checking ripeness, colour, and storage appropriateness of fruits and vegetables; detecting flaws, bruising, and diseases of fruits and vegetables; and assessing mycotoxin contamination from fungi, such as *Aspergillus flavus* in maize and peanut kernels are all examples of quality control in the food sector. Sensors and high-throughput platforms thrive in highly regulated environments. The sorting and grading procedures necessitate real-time decision-making based on sensor data. Thus, for carrying out such operation smoothly, sensor-based data appreciably increase the shelf life of marketable products.

Disease sensing and data processing

Options for recording the technical sensor data on disease manifestation are gaining popularity. The availability of structural and physiological features of tree tops damaged by insect pests and fungal infections is likely to be enhanced by spectral information and 3D data from remote sensing. Chlorophyll fluorescence, spectrum imaging, thermal imaging, and LiDAR are common sensor systems. Lateral flow microarrays, biosensors, spectroscopy, and remote sensing are common techniques used for disease identification and severity assessment. Non-invasive approaches such as X-ray fluorescence, soft X-ray fluorescence, and neutron activation analysis are used for disease identification and severity assessment. Remote sensing techniques are used for disease identification and severity assessment using correlation and regression analysis. The generation of disease-specific indices using remote sensing data is a common method used for data processing. Machine learning methods are used for disease identification and severity assessment. Automated machine learning methods provide a range of uses, from disease monitoring to disease management. Reproduction, dissemination, and overwintering are key stages in the life cycle of a pathogen. A thorough understanding of both methodology and biology is needed for effective disease management.

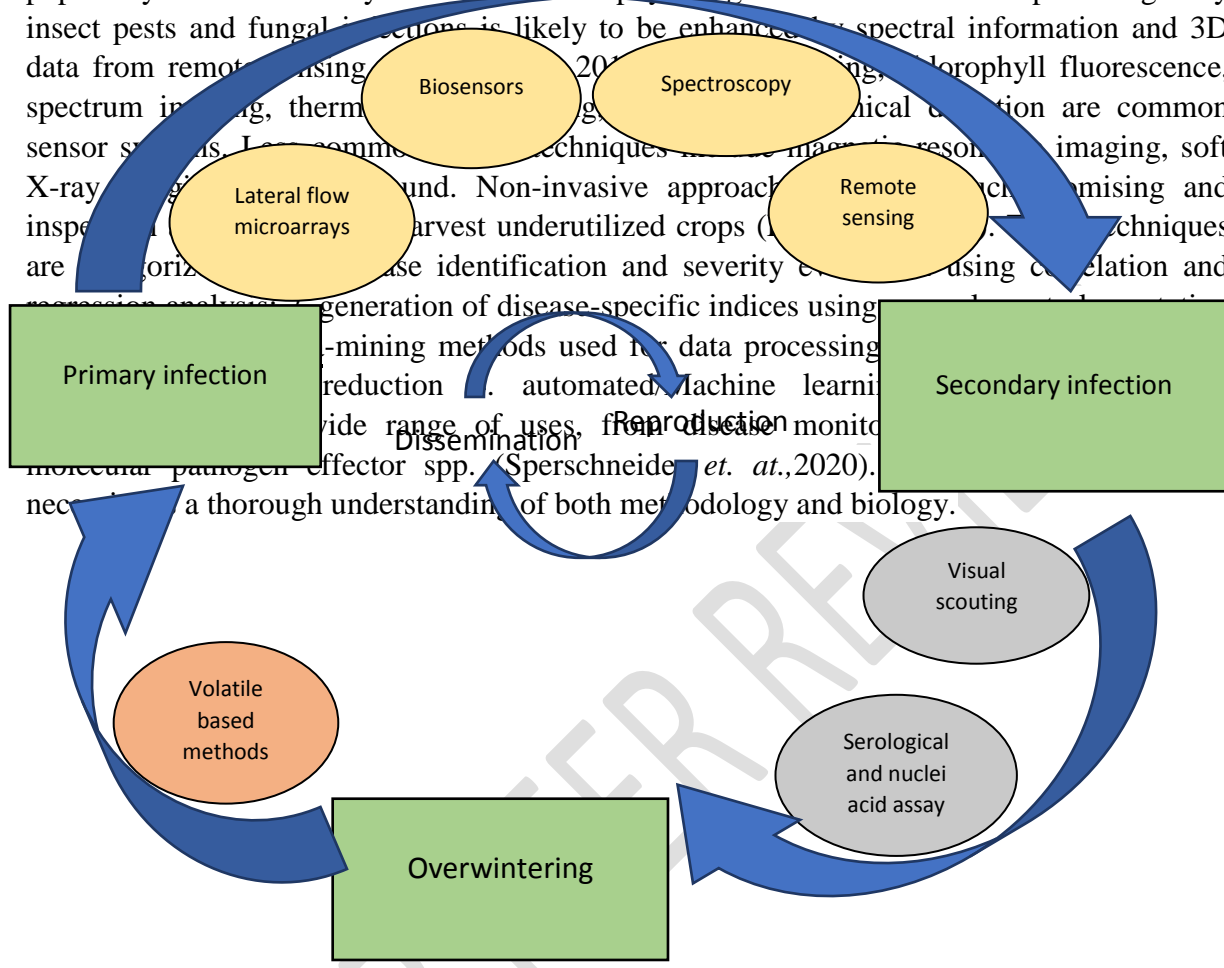


Fig.2: Methods indicated for time of detection and diagnosis of Polycyclic diseases

Sensor used for plant disease

Sensors are classified by (1) the electromagnetic spectrum range they cover, such as visible (VIS), near-infrared (NIR), short-wave infrared, thermal infrared, and radar; (2) the scale/platform they operate on, such as remote sensing stricto, airborne and spaceborne, UAV, ground-based/proximal, and microscopic; and (3) the recording principle they use, such as passive sensors that record radiation emitted by an object (thermography) or solar radiation reflectance (RGB, spectrum cameras)—active sensors,[LIDAR (light detecting and ranging), SAR (specific absorption rate), fluorescence] emit a unique detecting radiation and recording its changes as a result of interactions with the target object—(4) the type of data recording (imaging vs. non-imaging)(Oerke *et. at.*,2018).

Spectral information

Imaging systems with spatial resolutions ranging from a few hundred to millions of pixels per image can record (a) one waveband or the sum of all wavebands in the 400–700 nm spectrum (panchromatic); (b) the three primary color components red, green, and blue (typical bandwidth 60–80 nm, e.g., smartphone RGB cameras); and (c) additional (NIR) bands (multispectral, discrete, and somewhat ambiguous). (d) narrow spectral bands over a continuous spectral range (hyperspectral, narrow wavebands 1 nm spectral resolution). As opposed to RGB data, hyperspectral data has additional spectral information. Each pixel is a vector with a dimensionality equal to the number of wavebands recorded. The implications of scale and environment on collecting and analyzing hyperspectral data on plant diseases and translating this technology from controlled circumstances to the field were explored by Thomas *et. at.*, (2018). Under normal growing conditions, powdery mildew, for example, is virtually undetectable. Thermography may be ideal for pre-symptomatic detection of pathogen activities within plant tissue because this passive technology is susceptible to early changes in transpiration (Mahlein *et. at.*,2016; Oerke *et. at.*, 2011).

Thermography

“Infrared thermography is a technique for determining the surface temperature of leaves, plants, or crop canopies based on their water status, particularly stomatal and cuticular transpiration” (costa *et. at.*,2013). “Root infections, reduced water movement within stems, changing stomatal aperture, and changes in cuticular conductance are diseases impacting the plant's water status that can be detected thermally” (Oerke *et. at.*,2018).

Fluorescence of Plants

“Pathogen attack affects the plant's photosynthetic apparatus, such as pigments, the electron transport chain, and Calvin cycle enzymes, either directly (necrosis) or indirectly (feedback regulation of the electron transport chain) by reducing photosynthetic leaf area and chlorophyll degradation (chlorosis) chain of transportation. For high-throughput phenotyping, a combination of pulse–amplitude–modulation chlorophyll fluorescence systems and image analysis utilising dark-adapted plants was suitable for assessing the impacted leaf area” (Rousseau *et al.*,2015). “As early as four days after inoculation, fluorescence spectra were beneficial in distinguishing brown rust–infected tissue from healthy wheat tissue” (Tischler *et al.*, 2018). Similarly, the quantum yield of photosystem II and nonphotochemical quenching could be used to identify the reactions of barley genotypes with different levels of resistance to *Blumeria graminis* f. sp. *hordei* (Brugger *et al.*, 2018).

Electronic Nose

Plants on Disease and insect manifestation emits various Volatile Organic Compounds (VOC). “E-noses can detect (some of) these VOCs; for specific applications, gas chromatographic headspace analytics or tailored commercial e-noses (e-sensing) are available. Disease-specific VOCs of fire blight of apple, grey mould of tomato, and powdery mildew of tomato have been found as phenylethyl alcohol, -copaene, and fluoro-aliphatic hydrocarbons, respectively” (Wilson *et. at.*, 2018). “Also, E-noses are used to monitor food quality and production operations and detect fruit and vegetable post-harvest infections”. [30]

Gathering other information by sensors

“Plant illnesses and products can be detected using nuclear magnetic resonance (NMR) and X-ray imaging techniques” (Sankaran *et al.*, 2015). “Internal bruising and Spraing disease signs in potato tubers were investigated using NMR imaging, as well as the difference between belowground damage caused by *Heterodera schachtii* and *Rhizoctonia solani* in sugar beets” (Thybo *et al.*, 2004; Hullnhutter *et al.*, 2012). “An additional underlying layer of melon seeds infected with Cucumber green mottle mosaic virus was discovered using optical coherence tomography” (Lee *et al.*, 2011). “Similarly, on persimmon leaves, biophotonic examination with a 1,310-nm swept-source optical-coherence tomograph effectively detected morphological variations between healthy leaves and those with round leaf spots” (Wijesinghe *et al.*, 2016).

Ground-based systems

“Despite the development of effective sensing techniques and technologies, most still require a controlled environment for data gathering to prevent false positives. An autonomous ground-vehicle robot designed for high-throughput in-field agricultural row-crop phenotyping was used to evaluate plant height and canopy closure data using the normalised difference vegetation index (NDVI) assessment using HIS” (Underwood *et al.*, 2017).

Conclusion

The ability of remote sensing systems to detect plant diseases varies. Although highly sensitive to pathogen-induced changes in plant metabolism, chlorophyll fluorescence, and thermography lack the ability to identify illnesses and distinguish them from abiotic symptoms and effects from arthropod activities (Oerke *et al.*, 2014). Spectral data, when combined with spatial data from photos and data on VOCs generated by diseased plants, appears to be useful for disease detection and categorization. However, thermography and fluorescence can be employed in crop monitoring to detect anomalies, followed by a visual check of problematic plants or locations.

Sensing is a tool for determining the severity of a condition, not a requirement or an active control mechanism for disease treatment. Sensors cannot replace the use of fungicides and mechanical disease control devices. Still, they can help direct (and focus) the actuator(s) to the plants or areas that need attention, hence assisting in reducing the amount of chemicals used. It is feasible to detect polycyclic diseases when effective curative treatment alternatives, such as systemic fungicides, are available. Sensors can be used to estimate disease-related production losses, determine which plants should be removed from the cultivated area, and evaluate which sections of the field should be kept uncultivated in the growing season due to

the presence of soilborne diseases that are resistant to other methods of management, such as crop rotation. However, employing these techniques in individual farms is costly. However, cumulative efforts for large cultivable areas with Governmental policies and individual deed successful results with low yield loss and high eco-friendly environment can be achieved.

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