



# Remote Sensing: A New Tool for Disease Assessment in Crops

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## Abstract

The continuous presence of plant pathogens, pests, and diseases affects the agriculture and forestry sector, which demands the need for highly potential and inexpensive methods for diagnosing and monitoring diseases of plants and pests. Based on the huge data obtained from the sensitive analysis and the various systems based on remote sensing, features related to remote sensing are identified, including VIS-NIR, sensitive analysis, characteristics of habitats, thermal and fluorescence parameters, and image- and landscape-based features. However, suitable areas for sensors have been incorporated for the precise and early detection of particular diseases, including field systems, screening for resistance, and assessing and evaluating reactions based on plant defense. Moreover, based on different sensors, remote sensing techniques vary significantly. These techniques assist in the detection and diagnosis of various major diseases. This chapter focuses on RGB camera, hyperspectral imaging, fluorescence spectroscopy, thermography, and multi-temporal-based remote sensing techniques used chiefly on diseases that significantly impact the agriculture economy.

## Keywords

Remote sensing · Imaging approaches · Features for plant diseases monitoring · Early disease detection

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### 3.1 Introduction

There is a need to enhance the yield of agricultural commodities to manage the requirement of the increasing population. It will not be possible to manage these requirements without the application of modern technologies (Mahlein et al. 2012a). Several abiotic and biotic factors reduce the yield of agricultural products such as viruses, fungi, animals, and arthropods. All these may be managed to some extent, but the losses due to abiotic factors may be significantly high. The estimated crop losses due to pathogens (oomycetes, viruses, bacteria, and fungi) are 16% worldwide (Oerke 2020). Monitoring plant pests and diseases at the right time is an important factor in solving these problems. In the last 80 years, the accuracy of visual disease assessment depends upon the conventional disease scales. Identifying the visual symptoms is most important for the accurate diagnosis of diseases. The assessment of the diseases with the emerging technologies gives accurate, reliable, and precise results.

During the last 30 years, the use of digital images and visible light imaging analysis increasing with time. The use of this software has become user-friendly and more sophisticated. For resolving the issues of disease management, remote sensing techniques show significant potential (Mahlein et al. 2018). The data obtained through remote sensing can recognize the crop conditions involving diseases and give information about the most effective strategy for management of diseases (Weiss et al. 2020; Liu et al. 2005). The meaning of the word “Remote” is far away. That’s why meaning of the “remote sensing” is the sensing of the objects from a distance. The term “remote sensing” is described by the ASPRS (American Society for Photogrammetry and Remote Sensing) as the technology, and science of gaining precise information about that thing which have physical appearance as well as about the environment, through the process of recording. It is also defined as the science and art of gaining information about a thing without establishing any physical contact. The procedure of remote sensing may be satellite, ground or aerial based (Gogoi et al. 2018). The remote sensing technology has two types.

1. Active (such as radar and LidDAR)
2. Passive (e.g., optical) remote sensing

In active remote sensing, the reflection of the emitted signals from the object is measured on the sensor and the object is irradiated from an artificial source of energy, e.g., radar.

In the passive remote sensing, the natural source applied to irradiate the object, for example, solar radiation, to detect the desired phenomenon.

In the passive remote sensing, there are different imaging cameras and detectors which are used to measure the reflection of the solar radiation that have wavelength of thermal infrared (3–15  $\mu\text{m}$ ), NIR (near infrared: 700–1100 nm) VIS (visible spectrum: 400–700 nm), and SWIR (shortwave: 1100–2500 nm), while in active remote sensing, the instruments used are LIDAR and Radar (Fahey et al. 2021).

The passive remote sensing is classified into two categories on the basis of using spectral resolution of sensor.

1. Multispectral remote sensing
2. Hyperspectral remote sensing

The use of hyperspectral remote sensing shows good potential in the passive remote sensing because it is non-destructive and non-invasive tool to monitor the abiotic and biotic plant stresses (Jones and Vaughan 2010). Hyperspectral imaging techniques offer various options to observe the disease at the initial stage, through the provision of early indicators in the form of minute variations in spectrum reflectance as a result of reflection or absorption. The small differences in canopies, individual plant or soil, can be more easily seen in hyperspectral images since they can provide comprehensive spectral profiles with hundreds of spectral bands. Therefore, hyperspectral images are used to resolve the large problems for timely and accurate determination of the physiological conditions of the crop. As a result of early detection, the outbreak and spread of the pests may be avoided on the important crops and it also reduces the consumption of pesticides which is harmful for the humans and their environment (Lucieer et al. 2014; Gonzalez-Dugo et al. 2015).

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## 3.2 History

The development of the camera over than 150 years ago led to the establishment of advanced remote sensing technologies. The practice and concept of looking down at the Earth's surface first developed when photographs from cameras attached to balloons were taken for the purpose of topographic mapping in the 1840s. Remote sensing (by application of visible spectrum) is started in 1909 in the form of aerial photography. In 1931, color infrared photography was started, and then it is widely used in forestry and agriculture. In 1950, Ms. Evelyn Pruitt first used the term "Remote Sensing" in the United States. Satellite remote sensing originally started as a dual method to photographing surfaces utilizing different sensors from spacecraft in the early stages of the space age (both American and Russian projects). In 4th October, 1957, Soviet was the first who launched man-made satellite named as "Sputnik 1" (Choudhary et al. 2022). In 1956, Colwell used the remote sensing technique to monitor the stem rust of wheat.

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## 3.3 Remote Sensing Techniques on the Basis of Different Sensors

### 3.3.1 Imaging Approaches

#### 3.3.1.1 RGB-Imaging

To assess the plant health, digital photography is an important technique in plant pathology. Red, green and blue images are called as RGB digital images in short form. The digital cameras are the simple source of red, green and blue (RGB) digital

images for quantification, detection, and identification of diseases and they are easy to operate. The technical factors of these simple digital cameras such as spatial resolution, digital and optical focus, or light sensitivity are increasing with the passage of time. In these days, nearly everybody carries a smartphone or tablet computer, together with a contemporary, powerful digital camera sensor, whether they are phytopathologist or a farmer. Alternative tools for analyzing digital photographs of various plant parts, from inflorescences to roots, include scanners or video cameras. Throughout the growth season, RGB sensors are utilized to monitor plants at every resolution scale.

The biotic stress of the plants have been detected by the using of RGB images with green, blue and red channels (Bock et al. 2010), including the data about the colors in LAB (A and B used for the adversary magnitudes that depend on the non-linear coordinates and L stands for lightness), RGB, HSV (stands for hue saturation value) color, YCBr (Y is the component of luma) and CR and CB are red and blue difference parts of chroma, respectively, and their special arrangement gives the information about the diseases of plants (Bock et al. 2010). Furthermore, variables for the detection and identification of plant disease signs include gray levels, colors, texture, connectivity, form factors, and dispersion (Neumann et al. 2014; Camargo and Smith 2009).

Many research teams have utilized machine learning and pattern recognition techniques to detect and diagnose diseases of plants by using RGB photos (Camargo and Smith 2009; Neumann et al. 2014). Additionally, the classification accuracy is improved by carefully choosing essential characteristics from the RGB pictures (Behmann et al. 2014). In the assessment of plant diseases, the analysis of digital images is important technology. There are different software packages such as “Leaf Doctor,” custom-made modules, ASSESS 2.0 and Scion image software are available (Pethybridge and Nelson 2015; Bock et al. 2010; Wijekoon et al. 2008; Tucker and Chakraborty 1997). In ASSESS 2.0, the histograms used as the foundation for the following thresholding are used to assess the color information of the photos. The user may modify the parameters for healthy and unhealthy regions through a well-organized graphical interface. Additionally, once the background has been removed from the item of interest, disease severity can be determined as a percentage or as infected pixels. The measurement of disease severity on single leaves and precisely ordered photos is particularly practical with ASSESS 2.0. The picture acquisition stage needs special consideration. Illumination, uniform focus, and sharpness are important for reliable and for getting accurate results through the analysis of images. Under the natural status, the quality of the image is dependent on the distance between the sensor and the object, pixel size, and the leaf orientation or image angle. Poor picture quality and heterogenic situations frequently lead to difficulties in recognition and low degree of accuracy.

### 3.3.1.2 Hyperspectral and Multispectral Reflectance Sensors

The classification of the sensors of spectral reflectance is based on the resolution of spectral (such as width and number of the bands which are measured), type of detector (such as non-imaging and imaging sensor), and their spatial scale. The

earliest spectrum sensors developed were multispectral ones. Typically, these sensors evaluate an object's spectral information across a number of somewhat broad wavebands. For instance, data from multispectral imaging cameras may be provided in the G, B, and R wavebands as well as in an extra near infrared band. The development of current sensors in hyperspectral imaging tools with a spectral range between 350 and 2500 nm and a potential of the spectral resolution below 1 nm enhanced the complexity of the measured data (Steiner et al. 2008). Sensors of hyperspectral imaging tools give both spatial and spectral information for the observed things, in contrast to non-imaging, which average the spectral information across a specific region.

Large matrices containing spatial  $y$ - and  $x$ -axes and spectral data as reflectance intensity for each waveband in the 3d space,  $z$ , can be used to show hyperspectral data. The distance between the sensor and object has a significant impact on the spatial resolution. That's why, spaceborne or airborne, far range system contains low level of spatial resolution as compared to the microscopic or near range systems. The spatial resolution has significant role in the detection of plant-pathogen interaction and in the identification of plant pathogens (West et al. 2003; Mahlein et al. 2012b). Field patches that are affected by the soilborne pathogens can precisely detected by the airborne sensors (Hillnhütter et al. 2011) or at the later stage of the disease (Mahlein et al. 2012a; Mewes et al. 2011) or the identification of single symptoms or infected plants and leaves, sensors with a spatial resolution of around 1 m are scarcely acceptable; proximal sensor system is preferred in these situations (West et al. 2003; Oerke et al. 2014). Despite numerous studies, the use of innovative hyperspectral imaging technology to plant pathology and the evaluation of disease severity is still in the early stages of development (Bock et al. 2010). The optical properties of the leaves are described by the absorbed light by the chemicals of leaves (sugars, water, amino acids, and lignin) reflection of light through leaves surface and from their internal structures and transmission of light through a leaf.

Therefore, reflection of light from the plant surface is a complex procedure that depends upon the many biochemical and biophysical interactions. The SWIR (1100–2500 nm) depends upon the composition of water and leaf chemicals, VIS (visible range 400–700) is influenced by the pigment content of the leaf, and NIR (near infrared reflectance 700–1100 nm) mainly influenced by the leaf structure, absorption by the water of leaf and internal scattering process of the leaf (Jacquemoud and Ustin 2001; Carter and Knapp 2001). When a highly specific plant disease or plant pathogen causes changes in reflectance, such as the sequence of necrotic and chlorotic tissue or the presence of typical fungal structures like powdery mildew conidia and hyphae or uredospores of rust, those changes can be described by difficulties in the structure of leaf and chemical composition of the tissues.

During the infection, the obligate fungus parasites such as rusts and powdery mildews have comparatively low effect on the chlorophyll composition and tissue structure as compared to the other pathogens such as, pathogens that are cause of leaf spot, mainly cause the degradation of tissues due to the production of pathogen-related specific enzymes or toxins and their results is in the form of necrotic lesions.

In opponent, rusts and powdery mildews fungi form their structures on the leaf that can induce the optical characteristics of plant–pathogen contact (Ul-Haq and Ijaz 2020a, b). By using semi-thin parts of diseased leaf portion and raster electron microscopy, complex and distinctive relationships for sugar beet leaf diseases are exemplarily observed. The highly distinctive and unique pattern of the disease enables the recognition of the disease based on the spectral characteristics of the plant. It is described that the variation of foliar pathogens depends on the reflectance from the leaf in the case of sugar beet (Mahlein et al. 2010, 2013). Based on these studies, Rumpf et al. (2010) were capable to identify sugar beets that were infected with rust, powdery mildew, and *Cercospora* leaf spot before any typical symptoms appeared. Non-invasive spectral data have been beneficial for monitoring *Fusarium graminearum* in wheat and other plant–pathogen systems (Bauriegel et al. 2011), *Phytophthora infestans* of tomato (Wang et al. 2008), or *Venturia inaequalis* in the apple (Delalieux et al. 2007). It was also shown that hyperspectral imaging technique to be helpful in the assessment of pathogens that producing toxins in the maize crop (Del Fiore et al. 2010).

Additionally, in-field spectral imaging was employed by Bravo et al. (2003) for the early identification of wheat with yellow rust infection, Hillnhütter et al. (2011) effectively differentiated between soilborne diseases by examining the symptoms brought on by the soilborne fungus (*Rhizoctonia solani*) and nematode *Heterodera schachtii* in fields of sugar beet. Apan et al. (2004) used EO-1 Hyperion hyperspectral imaging technique to identify orange rust on sugarcane. Later, Huang et al. (2007) used aerial hyperspectral imaging and ground-based spectral measurements to identify yellow rust in wheat crop. Hyperspectral imaging technique is also widely applied for the observation of fruit quality and health along with the identification of plant pathogens during the vegetative period of the crop. By using hyperspectral imaging tool, defects on the surface of apple (Mehl et al. 2004), rot disease of strawberries (ElMasry et al. 2007), and canker lesions on the citrus fruit can be identified (Qin et al. 2009). These methods are useful for avoiding storage infections of crops and screening fruits.

### 3.3.1.3 Thermal Sensors

IRT stands for infrared thermography which measures temperature of plants and has relationships with crop microclimate, variations in transpiration rate caused by early plant–pathogen infections, and plant water status. Infrared and thermographic cameras are able to detect infrared radiation that is emitted in the thermal infrared range between 8 and 12  $\mu\text{m}$ , which is represented in false color photographs with each image pixel including the value of temperature of the observed thing. Infrared thermography may be used at the different spatial scales and temporal from small scale to airborne applications. However, it is mostly depending on the environmental conditions such as sunlight, wind speed, rainfall, or ambient temperature. The transpiration of the plant shows close relationship with the leaf temperature, which is affected in different ways by the variety of pathogens. While many other foliar pathogens such as rusts or leaf spots bring well defined and local changes, damaged

by the plant root pathogens such as *Pythium* spp. or *Rhizoctonia solani*, or systemic infection that mostly induce water flow in all parts of plants and transpiration rate.

It is reported that the temperature changes in plants are due to the infection caused by the pathogens or due to the defense mechanism of the plant. By using IRT technique, successfully monitored the downy mildew of cucumber (*Pseudoperonospora cubensis*) or apple scab (*Venturia inaequalis*). The variability between and among leaves can be used for efficient IRT image analysis. A major predictor of the emergence of plant disease is the mean temperature differential within individual leaves, crops, and plants.

#### **3.3.1.4 Fluorescence Imaging**

Different parameters of chlorophyll fluorescence have been used in the determination of plant photosynthetic activity. Chlorophyll fluorescence imaging devices are frequently active sensors that measure photosynthetic electron transport using laser light or LED source. Fluorescence imaging is used to evaluate variation in plant photosynthetic system due to the abiotic and biotic stresses on the leaf surface. Combining the image analysis and fluorescence imaging techniques to be useful in the quantification and determination of fungal infection. In order to assess plant disease at the field or canopy level, research has focused on collecting fluorescence characteristics from sun-induced reflection in the field (Mahlein 2016).

### **3.3.2 Non-imaging**

#### **3.3.2.1 Vis-NIR Spectroscopy**

Visual infrared-near infrared spectroscopy (VIS-NIR) is a rapid and non-destructive procedure which provides prediction of biological and chemical composition of the system. The Vis technique of the spectroscopy can examine the pigment and color analysis, while NIR is used to measure the quantity of macro components, mostly water. The visible region that ranges between 400 and 700 nm can provide data on the basis of spectral features of pigments and it is also used during the photosynthesis process of the plants. In these pigments, anthocyanin, carotenes, and anthocyanin are involved that induce the color appearance and can show disease in trees and plants. Each pigment has specificity in spectrum absorption such as the green region absorbs 530–550 nm wavelength light which is due to the presence of anthocyanin, and due to the presence of carotenes, range of the light wavelength is 420–503 (Zahir et al. 2022).

#### **3.3.2.2 Fluorescence Spectroscopy**

Fluorescence spectroscopy is a procedure which is applied to determine the fluorescence of the substance after reflection along a beam which is usually ultraviolet and having wavelength 10–400 nm. The fluorescent material has unique color that only visible when comes in the front of UV light since the absorbed light is undetectable to the human eye while the released light is in the detectable range. The mechanism of this procedure is involved using a light beam that induce the electrons in

molecules of a substance and as a result light is emitted. FS has wide range of applications. FS is used to monitor the stress levels and physiological states of the plants. Generally, the use of FS tool in plant study, especially in nutrient deficiencies and plant diseases has gain more attention. The FS procedure applied as a tool determines and senses the pathogens of plant at their initial stage. For instance, FS has been used to determine the plant–pathogen interaction in leaf rust and powdery mildew of wheat, spring barley, to identify the cucumber disease, and to quantify and identify the infection of banana due to the *Fusarium oxysporum* f. sp. *cubense*.

There are several devices of FS that have used to observe and gain information from plant specimens. In these devices, fiber optic fluorescence spectrometer, portable multiparametric sensor, and imaging multispectral fluorescence are involved. However, the most reliable and accurate FS device to detect plant pathogens is the fiber optic fluorescence spectrometer in contrast to other devices. There are four emitted wavelengths used in the FS, that are Green (G), Red (R), Blue (B), and UV and the excited FS is observed in red RF, far red RF, and yellow YF.

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### 3.4 Remote Sensing Features for Plant Diseases and Pest Monitoring

Agriculture and the forest sector are highly threatened by the ongoing progression of plant diseases and pest attacks globally (Oerke 2006; Strange and Scott 2005). Plant protection practices must be guided by knowledge about the location, scope, and severity of disease and pest incidence. Techniques and approaches based on remote sensing (RS) might be a prime addition that has the capability to monitor and diagnose diseases on plants as well as on pests, an extensive scale because standard field searching of pests and diseases on plants is quite effortful, liable not to be impartial, and typically exhibits minimum proficiency (Mahlein 2015). Methods of “radiodiagnosis” of plants that effectively provide contact-free and at a global level constant monitoring and examining of pests and diseases on plants that could be viewed in the remote sensing of pests and diseases on plant diseases.

With regard to the efficient detection or monitoring of pests as well as diseases, numerous systems of RS are accessible that can be applied efficiently to possibly monitor the progression of the disease. These RS systems provide data collection ranging from gamma-ray to microwave radiations, working with both radiations that are either passive or active. Many struggles have been brought to action for various RS systems in detecting the infection symptoms such as blights, pustules, and scabs, structural changes such as landscape structure, canopy structure, and physiological responses such as changes in water content, pigment content, caused by pests and diseases on plants in order to effectively detect and monitor pests and plant diseases (Hahn 2009; Sankaran et al. 2010; Mahlein 2015).

It is essential to recognize useful and distinguishing RS characteristics and features in order to employ RS-based observations in monitoring and examining pests and plant diseases. Until now numerous RS-based features and attributes have been suggested or discovered for identifying plant pests and diseases as well as for



identifying their natural environment. The primary RS-based features involve features based on the landscape as well as image-based features for thermal and fluorescence systems, and VIS-NIR spectral characteristics. Considering that different diseases and pests have different damage processes, a precise and accurate assessment of RS characteristics is typically required to provide efficient monitoring (Mahlein 2015).

### 3.4.1 VIS-NIR Spectral Features

VIS-NIR spectral features are extensively employed since VIS-NIR sensors are considered widely used systems based on RS for tracking pests and plant diseases. The most basic version of these properties is band reflectance. The majority of researchers have found that several diseases of plants and pests are sensitive to the green, red, and NIR spectral areas. There are several approaches to altering the values of spectrum reflectance, including continuous wavelength transformation, spectral derivatives, and continuous removal transformation.

**Spectral derivative transformation** is generally executed to apprehend convex features of the spectral measurement of plants which includes red edge position and amplitude.

**The continuous removal technique** is usually used for the quantitative characterization of both the convex and concave traits of the plant's spectra performed along the spectrum in a precise absorption location, which can be employed efficiently for the diagnosis of many plant diseases mainly wheat powdery mildew and tomato leaf minor (Xu et al. 2007; Zhang et al. 2012).

**Continuous wavelet analysis** or CWA has been employed for the identification and detection of many pests and diseases on plants (Cheng et al. 2010; Luo et al. 2013). CWA-derived features outperform certain traditional spectral-related features in identifying winter yellow rust of wheat due to their ability to capture some subtle changes in spectral shape (Zhang et al. 2014).

### 3.4.2 Fluorescence and Thermal Parameters

For the diagnosis and identification of numerous pests and diseases in plants associated with thermal and fluorescence sensors, some variables and parameters have been set to create an efficient linkage between the symptoms of infection and signals based on thermal and fluorescence sensors. For the diagnosis of the presymptomatic state of a pathogen, some researchers have used the ratio by dividing the fluorescence amplitude such as  $F_{686}/F_{740}$  on the basis of continuous fluorescence spectra with the addition of fluorescence peaks (Bürling et al. 2012; Tartachnyk et al. 2006; Kuckenberger et al. 2009). Additionally, a number of fluorescence parameters were used in the detection of pests and plant diseases based on the saturation pulse fluorescence analysis, including the non-photochemical quenching

(NPQ), the highest potential in light-adapted material of PSII photochemistry ( $Fv'/Fm'$ ), the efficiency of photosystem II (PSII) in terms of quantum yield and the maximal quantum efficiency of primary photochemistry photosystem II (PSII) ( $Fv'/Fm$ ) (Cséfalvay et al. 2009; Scholes and Rolfe 2009; Iqbal et al. 2012). Characteristics which are produced from sensors based on thermal infrared for detecting pests and diseases on plants are reasonably easy to understand and less complex than spectral features and fluorescence features. In essence, the canopy and leaf temperatures have been considered quite significant signals. The differential temperatures between the air and leaves ( $T_{leaf} - T_{air}$ ) in a controlled environment such as a greenhouse were discovered to be useful in identifying presymptomatic *Plasmopara viticola* infection in grapevines (Stoll et al. 2008).

### 3.4.3 Image-Based and Landscape Features

For monitoring and surveying diseases on plants and pests, imaging observation can be obtained and examined based on distinct systems of RS such as fluorescence, thermal and VIS-NIR systems. Using the features such as texture and landscape, the precise evaluation of the severity and in-depth disease mapping of the area where infection occurs can be done efficiently (Bauriegel et al. 2011). To extract texture features from images, including uniformity, variance, mean intensity, correlation, contrast, modus, product-moment, entropy, inverse difference, and information correlation, the colour cooccurrence method (CCM) is frequently used which are crucial especially at the micro (leaf) level for identifying plant diseases and pest (Donohue et al. 2001; Shearer and Holmes 1990). Yao et al. (2009) suggested the classification of rice blast, rice bacterial leaf blight, rice sheath with 97.2% of precision based on the group of shape and texture traits. Some spatial measurements such as landscape features bring out from the RS images. Moreover, the features based on the texture of image can identify the pattern based on spatial and geographic distribution for pests and plant diseases and provide helpful information in their extensive such as regional and plot monitoring. In addition to the features based on optical, thermal, fluorescence and last but not least image-based offers a different viewpoint for keeping track of pests and plant diseases.

### 3.4.4 Features Associated with Habitat Characteristics

A few attempts have been done to use data based on RS to define the suitability of the habitat of the pests and the plant pathogens, irrespective of the traits of RS that cannot be indirectly associated to losses brought on by pests and plant diseases. Given that stressed plants are frequently more vulnerable to disease and insect attack, the Tasseled Cap Transformation (TCT) based metrics such as brightness, greenness, and wetness linked with soil moisture and vigor and vitality of plant were found to be an effective substitute for habitat fitness (Coops et al. 2009; Zhang et al. 2013; Wolter et al. 2008). Regardless of the metrics based on TCT, LST, and Vis, are

effectively employed to give substantial and vital information for habitat state description. In the efficient monitoring and observation of mosquitoes larvae, tree woolly adelgid, wheat powdery mildew, and spruce budworm, several VIs such as MSI, WI, PRI, SAVI, MSAVI2, NDWI, and TVI connected with biomass, water contents, and concentrations of pigments are highlighted (Brown et al. 2008). The land surface temperature which is used to monitor the rated intensity of transpiration in plants is easily accessible from products obtained from satellite imagery such as MODIS-LST or it can be recovered from many satellites of thermal bands such as HJ-IRS, Landsat TM, and ASTER. Suitable habitat for the monitoring of disease and pests can be obtained with 82% of verified precision. Assimilation of RS features and parameters of meteorology together constructed the disease forecasting model (Zhang et al. 2013). An accuracy of 69–78% of their results suggested that adding up information related to RS efficiently improves the level of precision for plant disease and pest monitoring.

### 3.4.5 Sensitivity Analysis for Selection of Features

It is a prerequisite step always that is required to do a sensitivity evaluation to determine the best feature of RS for the monitoring and examination of pests and diseases on plants since they may produce noticeably distinct symptoms and differing environment characteristics. In order to do this, statistical techniques have been used to evaluate feature sensitivity. Analysis of Variance (ANOVA) and independent *t*-tests were widely employed, for instance, to categorize different types of illnesses and pests or to distinguish between different infection levels (Yuan et al. 2014; Zhang et al. 2012). For RS features identification, the Pearson correlation analysis is considered the most favored and highly sensitive technique of analysis (Huang et al. 2012; Zhang et al. 2012, 2014). Yang et al. (2007) found that the sensitivity band for detecting rice leaf folders drastically changed from tillering stage at 757 nm to the heading stage at 445 nm. Furthermore, it is important to keep in mind that sensitivity features may differ across observation scales.

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## 3.5 Relevant Areas for Sensors in Plant Disease Detection

Plant pathologists have access to a wide range of sensor technologies that may offer high and accurate resolution data on agricultural crops and serve as the foundation for the on-time detection and diagnosis of diseases on plants. It is astonishing how far these technologies have come in the last 40–50 years in terms of development and application to agriculture as well as detection and monitoring of plant disease (Brenchley 1964; Nilsson 1995; Jackson and Wallen 1975; West et al. 2003; Seelan et al. 2003). Latest and customized techniques for solving plant and agricultural science-related problems have been created as a result of developments in plant phenotypes and agriculture (Cobb et al. 2013; Fiorani et al. 2012). The most effective sensors are now being employed for non-invasive field assessments of

crop nutrient status. In agriculture, practical base future applications will benefit from the development of new, low-cost sensor technologies that perform satisfactorily and are now on the market (Grieve et al. 2015). There are equipment and technical options for phenotyping in the field, greenhouse, and other environments. However, they cannot be used widely because these are highly customized and specialized prototypes.

### 3.5.1 Field Systems

The imaging platform developed by Polder et al. (2014) for the diagnosis and detection of Tulip breaking virus (TBV) which usually infects bulbs of tulip flowers, or the monitoring and detection of the wheat yellow rust caused by *Puccinia striiformis* hyperspectral imaging platform prototype developed by Bravo et al. (2003) are two examples of cutting-edge systems with potential field applications. A robot with multispectral sensors and pipelines for mechanized vision online evaluation was created by Polder et al. (2014). There were not many technical specialists available to rate tulip bulbs, which motivated this study. This technique was able to be optimized and adjusted to reach a degree of precision comparable to that attained by seasoned rating experts. Under light ambient conditions, the yellow rust disease of wheat can be able to detect and categorize in fields successfully with a rate of 96% using the hyperspectral imaging “buggy” of Bravo et al. (2003). Their findings are highly promising for the establishment of optical sensor systems that are both affordable and accurate for the early plant disease detection in various crops.

### 3.5.2 Resistance Screening

Different technological techniques have been created for plant phenotyping. The process of development began with controlled investigation and examination of individual plants (Chaerle et al. 2007; Jansen et al. 2009). Improved field systems have lately quite durable, allowing for a comprehensive evaluation of plant execution and performance across many plots or throughout the whole canopy of plants (Walter et al. 2015). It has been demonstrated that optical sensors can assess the degree of sensitivity and/or resistance of various genotypes and variants to a particular disease. By using multispectral and fluorescence imaging, Chaerle et al. (2007) contributed by distinguishing lines of sugar beet with varying degrees of sensitivity to *C. beticola*. In order to assess the symptoms on *Phaseolus vulgaris* by *Xanthomonas fuscans* subsp. *fuscans*, depends on the chlorophyll fluorescence metrics *Fv/Fm* on picture pixels Rousseau et al. (2013). Additionally, more contemporary innovations were produced, such as the HyperART system for concurrently monitoring and observing leaf transmission as well as leaf reflectance (Bergstrasser et al. 2015). In a preliminary application study to evaluate different sugar beet resistance/susceptibility levels to *C. beticola*, this sensor device showed potential. It has been demonstrated that extra data from the measurements during transmission

boosts the sensitivity of detection; nevertheless, the measurement methodology and procedure are fairly complicated and still call for a significant amount of human work.

### 3.5.3 Assessment of Plant Defense Reactions

The majority of research has been published on the subject of detection and diagnosis of plant disease systems which are dependent on symptoms, biochemical, and the changes that occur physiologically prior to symptoms. In the screening of resistance, pathologists are interested in minute defensive responses that are essential for plants' capacity to pathogen invasion or restrain pathogen growth. Robinson (1969) defined resistance in the host as a plant genotype's capacity to impede a pathogen's growth and/or development. Long recognized as two broad forms of resistance, qualitative resistance is controlled by a single gene (complete or vertical resistance), and quantitative resistance is controlled by numerous genes with partial effects (incomplete or horizontal resistance). A significant range of defensive mechanisms are activated by plants in response to pathogen infection (Glazebrook 2005). These strategies include the synthesis of proteins and antimicrobial metabolites, the formation of callose and lignin to physically strengthen cell walls, and the stimulation of hypersensitive responses. Following the initial encounter with a pathogen, these changes take place at the level of tissue and cell and are necessary for eventually interactions either compatible or incompatible or, when examining the plant edges, for sensitivity or tolerance of a genotype or any disease. It is necessary to build particular sensors with a high and efficient spatial resolution in order to evaluate these extremely early and marginal changes. By integrating highly throughput DNA cloning and transformation techniques based on single cells adjusted with phenotyping and automated microscopy, Douchkov et al. (2013) developed a planned platform known as the "microphenomic." On several genotypes of barley, they were able to evaluate the penetration efficiency of fungus *Blumeria graminis* f. sp. *hordei*.

It is notable that in this instance, histological analysis of leaf portions that had previously been detached and decolored was employed. From digital pictures obtained from microscopical RGB, sites of fungal penetration and as feeding organs powdery mildew may be evaluated automatically and tallied. This extremely intrusive method only allows for the examination of a plant pathogen's interactions with its host plant at a particular time period. Generally, this enables distinguishing various types of resistance such as complete, incomplete, and partial resistance, whereas some portions impede a pathogen's penetration initially, others cause a hypersensitive reaction to reduce supply of nutrients to make the pathogen starved. Moreover, spore forming capability of pathogen is also restricted in some situation (Glazebrook 2005). Kuska et al. (2015) have created a technique for hyperspectral microscopic analysis. With this data-driven phenotyping technique and sensor-based system, evaluation of over time interactions between host and pathogen and the

differentiation of barley genotypes against powdery mildew in terms of varying susceptibilities were made possible on a small-scale basis.

### 3.6 Use of Different Remote Sensing Methods for Different Diseases

Based on various sensors, for monitoring and detecting pests and diseases on plants, generally remote sensor techniques involve two groups which are discussed as follows:

- **Imaging Approaches**
  - RGB camera
  - Imaging based on multispectral spectrum
  - Imaging based on hyperspectral spectrum
  - Thermal base imaging
  - Fluorescence-based imaging
- **Non-Imaging Approaches**
  - Spectroscopy of VIS and IR
  - Spectroscopy technique based on fluorescence

#### 3.6.1 RGB Camera

##### 3.6.1.1 Use of Airborne Remote Sensing for Plant Disease Detection

###### 3.6.1.1.1 ADAR System for the Detection and Diagnosis of Rice Sheath Blight Disease

Four aerial-based remote sensing photos were collected with the help of the ADAR (Airborne Data Acquisition and Registration) System 5500, Qin and Zhang (2005) in central Arkansas, USA identified the rice sheath blight disease. The pictures were divided into four bands: near infrared was included in band 4 with 780–1000 nm wavelength, red was in band 3 with 610–680 nm wavelength, green was included in band 2 with 530–600 nm wavelength, and blue was in band 1 with a wavelength of 450–540 nm. They compared the photos with the field disease index using three different techniques: the Direct Band Digital Number (DN) value, Standard Difference Indices (SDI), and Ratio Indices (RI). The findings suggested that RI and SDI may be used to remotely identify the pathogen that causes rice sheath blight (Qin and Zhang 2005).

### 3.6.2 Hyperspectral Imaging

#### 3.6.2.1 Early Detection of Wheat Yellow Rust Disease Caused by *Puccinia striiformis* by Using Hyperspectral Imaging

Hyperspectral base imaging in agriculture has increased significantly in recent years. The amount and information quality become increased by this technology's usage of narrowband sensors. The spatial Z-axis, a spectral X-axis, and a spatial Y-axis are

axes on which whole data is based. The complete information of wavelength is contained in each spatially situated pixel of a picture. For the purpose of early identification of the winter yellow rust disease (*Puccinia striiformis*) in wheat, Bravo et al. (2003) employed VNIR hyperspectral imaging. The full spectral range from 463 to 895 nm was covered by 19 wavebands that were each 23 nm or 30 pixels wide. They noticed that due to the disintegration of leaf structure internally, the symptomatic plants had increased reflectance in the visible spectrum (VIS) due to decreased activity of chlorophyll and in the near infrared (NIR) spectrum higher absorption was observed (Bravo et al. 2003).

### 3.6.3 Thermography for Plant Disease Detection

#### 3.6.3.1 Thermographic Assessment of Apple Scab Disease

Oerke et al. (2011) injected  $6 \times 10^5$  conidia/mL of the HS1 isolate of *V. inaequalis* onto apple leaves and monitored the results daily. They captured thermograms using a spectral sensitivity ranging from 8 to 12  $\mu\text{m}$ , Varioscan 3201 ST camera and by using IRBIS plus software pictures were then analyzed (Vers. 2.2, InfraTec.). Prior to the development of obvious scab signs, the researchers noticed that the leaves injected with *V. inaequalis* conidia had shown the appearance of concentric spots of very low leaf temperature (6 dpi). When the typical scab symptoms appeared at 8 dpi, the affected leaf area and difference of temperature from non-diseased areas increased, but the temperatures of apple leaves that were not infected varied little over space (Oerke et al. 2011).

### 3.6.4 Fluorescence Spectroscopy for Plant Disease Detection

#### 3.6.4.1 Early Detection of the Hypersensitive Reaction to Tobacco Mosaic Virus Using Multicolor Fluorescence Imaging

In the “Samsun NN” and “Sumsun nn,” the resistant and susceptible cultivars of tobacco plant, respectively, Chaerle et al. (2007) inoculated tobacco mosaic virus to observe the HR response and subsequent death of plant cells aggravated by TMV inoculation. A “Luminescence spectrometer LS52” equipped with a “Xenon flash lamp (FX-4400)” was used to excite the fluorescence. After 88 h of inoculation with TMV observation was started. Above 400 nm of wavelength, ultraviolet light as compared to the control induced blue fluorescence which considerably enhanced during the hypersensitivity response to tobacco mosaic virus infection. Towards the 550 nm range, the difference in fluorescence steadily diminished. The susceptible tobacco cultivar “Samsun nn” was not changed substantially in fluorescence emission by TMV infection (Chaerle et al. 2007).

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### 3.6.5 Multi-temporal Remote Sensing for Plant Disease Detection

#### 3.6.5.1 Use of Multispectral Remote Sensing for Multi-temporal Wheat Disease Detection

For the identification and detection of wheat leaf rust and powdery mildew, QuickBird satellite multispectral multi-temporal images with high resolution were used which are evaluated by Franke and Menz (2007) in Bonn, Germany. Mixture tuned matched filtering (MTMF) and NDVI techniques were used to classify the data. The initial scene's classification accuracy was 56.8%, but the subsequent scenes attained much better accuracies of 65.9% and 88.6%, respectively, as compared to the initial scene of classification accuracy (Franke and Menz 2007).

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## 3.7 Conclusion

For disease and pest management, large-scale growing of agricultural crop is the need of the hour for early disease diagnosis. In order to monitor and predict epidemics, remote sensing offers precise, non-invasive, accurate, quick, and reliable estimates of diseases. When used to identify illnesses in green plants, data obtained by hyperspectral remote sensing is collected from low altitudes and often has a great spectral and spatial resolution. Regional agricultural disease mapping has proved to be quite efficient for multi-temporal data based on remote sensing. The approach of categorization based on spectra can be used to identify agricultural diseases. When comparing the NDVI spectral profiles of healthy and diseased crops, a significant difference could be seen that indicated situation of crops under stress. To dramatically spatialize diagnostic results, remote sensing technology will be very beneficial. This will increase agricultural sustainability and safety by reducing the costly usage of pesticides for crop improvement and protection. A multidisciplinary approach involving engineering, plant pathology, and informatics is necessary to fully use the promise of these highly advanced, new technologies. The adoption and complete awareness of this approach will be enhanced by a solid decision support system via cross-disciplinary collaboration.

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