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Remote sensing and its use in detection and monitoring plant diseases: A review

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ABSTRACT

Remote sensing is a rapid, non-invasive and efficient technique which can acquire and analyze spectral properties of earth surfaces from various distances, ranging from satellites to ground-based platforms. This modern technology holds promise in agricultural crop production including crop protection. Variability in the reflectance spectra of plants resulting from occurrence of disease and pests, allows their identification using remote sensing data. Various spectroscopic and imaging techniques like visible, infrared, multiband and fluorescence spectroscopy, fluorescence imaging, multispectral and hyperspectral imaging, thermography, nuclear magnetic resonance spectroscopy etc. have been studied for the detection of plant diseases. Several of these techniques have great potential in phytopathometry. Remote sensing technologies will be extremely helpful to greatly spatialize diagnostic results and thereby rendering agriculture more sustainable and safe, avoiding expensive use of pesticides in crop protection.

Key words: Band, Plant disease, Remote sensing, Sensor, Spectral domain.

The worldwide demand for agricultural products exceeds the supply, hence there is a need to manage the production of agricultural commodities more efficiently. Without the use of modern technologies, it will be not feasible to work against this trend (Mahlein *et al.*, 2012). The use of innovative technologies like 'Remote sensing' holds promise in agricultural crop production including crop protection. It is a rapid, non-invasive and efficient technique which can acquire and analyze spectral properties of earth surfaces from various distances, ranging from satellites to ground-based platforms. In this review, remote sensing technique and some of its current studies in plant disease detection and monitoring are discussed.

What is remote sensing: The term 'Remote' means far away. So 'Remote Sensing' means sensing things from a distance. The "American Society for Photogrammetry and Remote Sensing (ASPRS)" defined photogrammetry and remote sensing as, "the art, science and technology of obtaining reliable information about physical objects and the environment, through the process of recording, measuring and interpreting imagery and digital representations of energy patterns derived from non-contact sensor systems." It is also defined as the art and science of acquiring information about an object without making any physical contact. The remote sensing technique may be ground, aerial or satellite based.

SCIENCE BEHIND THE REMOTE SENSING TECHNIQUE

Reflection pattern in healthy vegetation: There are three distinguished spectral domains of vegetation reflectance based on which remote sensing techniques are used (Fig 1). Sahoo *et al.*, (2015) discussed that spectral properties of vegetation are strongly determined by their biophysical and biochemical attributes such as leaf area index, the amount live and senesced biomass, pigment and moisture content and spatial arrangement of cells and structures. In the visible domain (VIS: 0.4-0.7 μm), the main light absorbing pigments are chlorophyll *a* and *b*, carotenoids, xanthophylls and polyphenols. Chlorophyll *a* displays maximum absorption in the 0.41-0.43 and 0.60-0.69 μm regions, whereas Chlorophyll *b* shows maximum absorption in the 0.45-0.47 μm range. These strong absorption bands induce a reflectance peak in the green domain at about 0.55 μm. In the near-infrared domain (NIR: 0.7-1.3 μm), absorption is very low and reflectance and transmittance reach their maximum values. This is caused by internal scattering at the air–cell–water interfaces within the leaves. In the mid-infrared domain (mid-IR: 1.3-2.5 μm), also called shortwave-infrared (SWIR), leaf optical properties are mainly affected by water and other foliar constituents. The major water absorption bands occur at 1.45, 1.94 and 2.7 μm and secondary features at 0.96, 1.12, 1.54, 1.67 and 2.2 μm (Sahoo *et al.*, 2015).

Reflection pattern in sick and dead leaves: Changes in reflectance result from modifications of biophysical and biochemical characteristics of plant tissue. When a plant is

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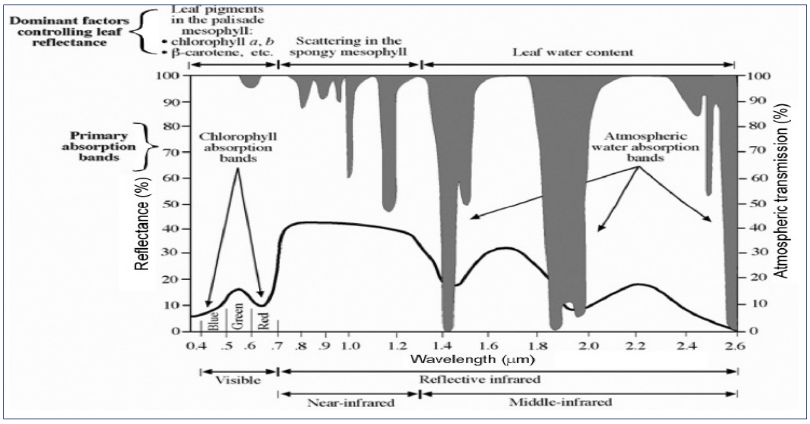

Fig 1: Three distinguished spectral domains of vegetation (Jensen, 2000, Sahoo *et al.*, 2015).

under stress, chlorophyll production may decrease resulting less absorption in blue and red bands in palisade cells. So along with green band, red and blue bands are also reflected. Hence, yellow or brown colour is developed in stressed vegetation. In stressed or diseased plants, NIR bands are not reflected by the mesophyll cells, instead they are absorbed by stressed or dead cells. As a result, dark tones are found in the image.

First use of remote sensing in plant pathological study in India: The use of remote sensing for national development started in India comparatively earlier than other developing countries. The first experiment that used remote sensing was on coconut root–wilt disease by Prof. Pisharoth Rama Pisharoty in Kerala in early 1970 (Dakshinamurti *et al*., 1971). Professor Pisharoty is regarded as the 'Father of Remote Sensing' in India, who was also the founder Director of the Indian Institute of Tropical Meteorology, Pune in 1962. In the coconut root-wilt study, Prof. Pisharoty *et al.* took aerial photographs with 'Hasselblad camera' in seven different combinations of wave bands from a helicopter flown at two different altitudes of 500 and 1000 feet. The photographic exposures included the colour Ektachrome infrared film, ordinary black and white film and black and white panchromatic plus X with three different filters in red, blue and green bands.

Remote sensing techniques based on different sensors: Based on sensors, the following two groups of remote sensing techniques are used in monitoring plant diseases:

1. Imaging approaches
- a. RGB Camera
- b. Multispectral imaging
- c. Hyperspectral imaging
- d. Thermal imaging
- e. Fluorescence imaging

2. Non-imaging approaches
- a. VIS and IR spectroscopy
- b. Fluorescence spectroscopy

Some other imaging techniques like Terahetz spectroscopy, X-ray imaging can also be used for detecting plant diseases; however all these techniques are not cost effective. Sankaran *et al.* (2010) reviewed the various imaging and non-imaging spectroscopic techniques used for monitoring diseases in various crops (Table 1 and Table 2). Again Mahlein (2016) reviewed the various optical sensors used in plant disease detection (Table 3).

AIRBORNE REMOTE SENSING IN PLANT DISEASE DETECTION

First use of aerial photography in determination of cereal diseases: Robert N. Colwell, University of California for the first time studied aerial photography in detail for monitoring black stem rust of wheat, oat and yellow dwarf of oat and published his work in the journal *Hilgardia* in 1956 (Colwell, 1956). Panchromatic, infrared and colour films (Aerial Ektachrome) were used in this study.

Detection of rice sheath blight disease using ADAR system: Qin and Zhang (2005) detected and monitored rice sheath blight disease at central Arkansas, USA using four airborne remote sensing images were acquired by ADAR (Airborne Data Acquisition and Registration) System 5500. The images had four bands: blue: band 1 (450–540 nm), green: band 2 (530–600 nm), red: band 3 (610–680 nm) and near infrared: band 4 (780–1000 nm). They used three methods for the comparison of images with the field disease index- 1) Direct band digital number (DN) value, 2) Ratio indices (RI) and 3) Standard difference indices (SDI). The results showed that RI and SDI had the potential to serve as indicators for remote identification of rice sheath blight disease (Qin and Zhang, 2005).

Aerial imaging platforms for identification of citrus greening disease: Garcia-Ruiz *et al.* (2013) compared the effectiveness of Huanglongbing (HLB) or citrus greening disease detection using unmanned aerial vehicle (UAV) sensor and aircraft based sensors yielding different spatial resolution (5.45 cm and 0.5m per pixel). A single engine fixed-wing aircraft was used for taking hyperspectral images

Table 1: Examples of studies on plant disease detection using imaging techniques (Sankaran *et al.* 2010).

Plant	Disease	Statistical methods	Optimum spectral range	Reference
Wheat	Scab (*Fusarium* head blight)	Step discrimination and discriminant analysis	568,715nm(550, 605, 623, 660, 697 and 733nm)	Delwiche and Kim (2000)
	Yellow rust, nutrient deficiency	Self-organizing map-neural network, quadratic discriminant analysis, regression analysis	680, 725 and 750nm	Moshou *et al.* (2006), Huang *et al.* (2007)
Tomato	Late blight disease	Minimum noise fraction transformation and spectral angle mapping-based classification	700-750nm, 750-930nm, 950-1030nm and 1040-1130nm	Zhang *et al.* (2005)
Grapefruit	Citrus canker	Principal component analysis	553, 677, 718 & 858nm	Qin *et al.* (2008)
Sweet orange	Blue mold, browning rot	Difference in reflectance	540 and 680nm	Sighicelli *et al.* (2009)

Table 2: Examples of studies in plant disease detection using non-imaging techniques (Sankaran *et al.* 2010).

Plant	Disease	Statistical methods	Optimum spectral range	Reference
Fluorescence spectroscopy				
Citrus	Citrus canker	-	452, 685 and 735nm	Belasque *et al.* (2008)
Visible and IR spectroscopy				
Wheat	Powdery mildew and take-all disease	ANOVA, correlation & regression	490_{780}, 510_{780}, 516_{1300} & 540_{1300}nm	Graeff *et al.* (2006)
Kiwifruit	Grey mold, *Sclerotinia* rot	Principal component analysis	-	Costa *et al.* (2007)
Grapevine	Grapevine leafroll disease (GLD)	Discriminant analysis	752, 684 and 970nm	Naidu *et al.* (2009)
NMR Spectroscopy				
Catharanthus roseus	Phytoplasma causing yellowing disease	Principal component analysis	-	Choi *et al.* (2004)

Table 3: Examples of studies on plant diseases detection by different 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)
	Tobacco	Anthracnose (*Colletotrichum destructivum*)	Wijekoon *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)
	Tulip	*Tulip breaking virus* (TBV)	Podler *et al.* (2014)
	Sugarcane	Orange rust (*Puccinia kuehnii*)	Apan *et al.* (2004)
Thermal sensors	Sugarbeet	Cercospora leaf spot (*C. beticola*)	Chaerle *et al.* (2004)
	Cucumber	Downy mildew (*Pseudoperonospora cubensis*), Powdery mildew (*Podosphaera xanthii*)	Oerke *et al.* (2006), Berdugo *et al.* (2014)
	Apple	Apple scab (*V. inequalis*)	Oerke *et al.* (2011)
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)
	Bean	Common Bacterial Blight (*Xanthomonas fuscans* sub sp. *fuscans*)	Rousseau *et al.* (2013)

with AISA (Advanced Imaging Spectrometer for Applications) Hyperspectral Imaging Sensor, EAGLE VNIR (397–998 nm). They observed that HLB-infected trees reflected higher amount of light in VIS region of the electromagnetic spectrum, while it was weaker than healthy trees in NIR region. UAV based sensor showed 67-85% classification accuracy while the accuracy was 61-74% in aircraft based sensor, indicating that UAV at low altitudes could become a low-cost and reliable tool for disease detection (Garcia-Ruiz *et al*. 2013).

HYPERSPECTRAL REMOTE SENSING IN PLANT DISEASE DETECTION

Hyperspectral imaging for the early detection of yellow rust disease in wheat: In recent years, hyperspectral imaging is gaining considerable interest in agriculture. This technology uses narrowband sensors increasing the quantity and quality of information. The information is based on the spatial X- and Y axes and a spectral Z-axis. Each spatially located pixel of an image contains the full wavelength information. Bravo *et al.* (2003) used VNIR hyperspectral imaging for the early detection of yellow rust disease (*Puccinia striiformis*) in winter wheat. They divided the acquired data into 19 wavebands, 23nm (30 pixels) wide, covering the entire spectral region between 463 and 895nm. They observed that the diseased plants showed higher reflectance in VIS region, because of lower chlorophyll activity and a higher absorption in the NIR region mainly due to internal leaf structure breakdown (Bravo *et al.*, 2003).

Utility of hyperspectral data for potato late blight disease detection: Ray *et al* (2011) investigated potato late blight in Amritsar, Punjab using hyperspectral data. They used 512-Channel Spectroradiometer (Fieldspec®Pro 2000) with a range of 325 to 1075 nm. The average reflectance spectra of potato crop under different level of disease infestation are shown in Fig 2. The hyperspectral reflectance curves showed that healthy plants have high reflectance NIR region (beyond 750 nm) and low reflectance in red region (around 650 nm). Once the disease intensity increases the NIR reflectance decreases and the red reflectance increases. Vegetation indices, namely Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Soil Adjusted Vegetation Index (SAVI) and Red Edge Index were calculated using reflectance values. The differences between the vegetation indices for plants at different levels of disease infestation were found highly significant. The optimal hyperspectral wavebands to discriminate the healthy plants from disease infested plants were 540, 610, 620, 700, 710, 730, 780 and 1040 nm whereas upto 25% infestation could be discriminated using reflectance at 710, 720 and 750 nm (Ray *et al*, 2011).

Hyperspectral imagery for mapping disease infection in oil palm plantation: Shafri and Hamdan (2009) used air-borne hyperspectral imaging (Sensor: Airborne AISA) for the detection of ganoderma basal stem rot disease in oil palm plantations.. A total of 10 vegetation indices and red edge techniques were used which could give accuracy between 73 and 84% (Shafri and Hamdan, 2009).

Detection of citrus canker using hyperspectral reflectance imaging technique: Qin *et al*. (2009) obtained 96.2 % classification accuracy using hyperspectral images (λ: 450–930nm) in citrus fruit affected by canker and other damages. They recorded that the values of the reflectance for the diseased peel conditions were consistently lower than those from the normal fruit surface over the entire spectral region. Canker had the lowest reflectance except for the spectral region from 450 nm to 550 nm, in which greasy spot showed similar reflectance with canker (Qin *et al*., 2009).

Spectral reflectance characteristics of healthy and Yellow Vein Mosaic (YMV) infected soybean leaves: Das *et al*. (2013) studied the spectral reflectance characteristics of YMV susceptible (JS-335) and tolerant (Pusa-9814) varieties of soybean crop at Indian Agricultural Research Institute (IARI) farm, New Delhi. They recorded the spectral data at 1nm intervals using ASD FieldSpec Spectroradiometer over a 350-2500nm wavelength range. They noted that the reflectance of healthy leaves was higher in NIR (0.8nm) and SWIR (0.55nm) region compared to YMV infected leaves (0.75nm and 0.45nm respectively). In VIS region the reflectance of YMV infected leaves (0.31nm) was higher than the healthy leaves (0.12nm). NDVI, Ratio Vegetation Index (RVI), Greeness Index (GI), Photochemical Reflectance Index (PRI) and Leaf Moisture Vegetation Index 1 (LMVI1) were computed and it was observed that NDVI was found to be useful in detecting yellow mosaic virus infected soybean (Das *et al*., 2013).

THERMOGRAPHY IN PLANT DISEASE DETECTION

Pre-symptomatic thermographic detection of cucumber downy mildew disease: Lindenthal *et al*. (2005), University of Bonn, Germany evaluated efficacy of thermography in pre-symptomatic detection of cucumber downy mildew, caused by *Pseudoperonospora cubensis*. They inoculated 5 ml of suspension of *P. cubensis* containing 1×10^5 zoosporangia/ml with a hand sprayer. Digital thermal images were obtained using a VARIOSCAN 3201 ST (Jenoptic Laser, Jena, Germany) with a spectral range from 8 to 12 μm. They observed that necrotization of infected leaves started at 5 dpi (days post inoculation) and reached almost 75% of leaf area at 6 dpi. The temperature distribution remained homogenous and MTD (Maximum Temperature Difference) was undistinguishable from that of non-inoculated leaves at 1 dpi; however, at 2 dpi, MTD of infected leaves was significantly higher (+0.6°C) than that of healthy leaves. With the development of downy mildew symptoms, MTD increased by more than 2.0°C at 5 and 6 dpi, about 1.4°C higher than for non-inoculated control leaves (Fig 3).

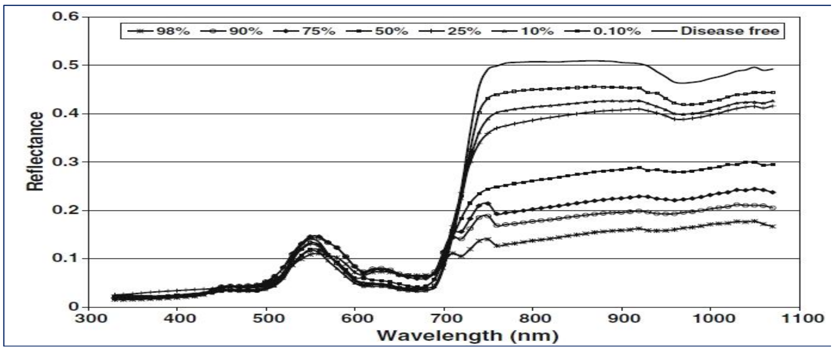

Fig 2: Reflectance of potato crop at different level of late blight infestation (Ray *et al.* 2011).

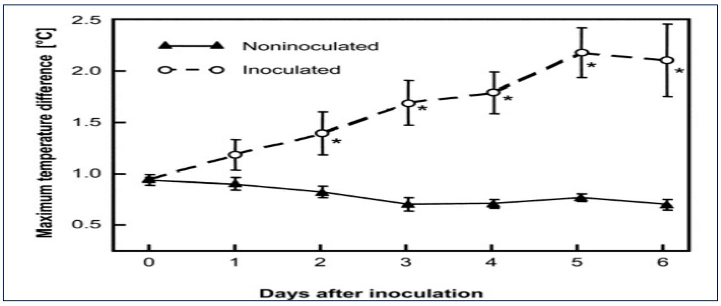

Fig 3: Maximum temperature difference of inoculated and non-inoculated cucumber leaf. Asterisks indicate means that differ significantly (*P=0.05)* (Lindenthal *et al.* 2005).

The slight decrease in MTD at 6 dpi coincided with an almost total destruction of leaf tissue by *P. Cubensis* (Lindenthal *et al*. 2005).

Thermographic assessment of scab disease (*Venturia inaequalis*) on apple leaves: Oerke *et al*. (2011) inoculated apple leaves with HS1 isolate of *V. inaequalis* with 6 X 10^5 conidia/ml and assessed daily. They used a a Varioscan 3201 ST camera with a spectral sensitivity from 8 to 12 ìm for taking thermograms and images were processed using IRBIS plus software (Vers. 2.2, InfraTec.). The researchers observed that the leaves inoculated with conidia of *V. inaequalis* showed concentric spots of unusual low leaf temperature even before the appearance of visible scab symptoms (6 dpi). The affected leaf area as well as its temperature difference from healthy areas increased at 8 dpi with typical scab symptoms, whereas the temperature of non-infected apple leaves showed little spatial variation (Oerke *et al*., 2011).

FLUORESCENCE SPECTROSCOPY IN PLANT DISEASE DETECTION

Multicolour fluorescence imaging for early detection of the hypersensitive reaction to tobacco mosaic virus: Chaerle *et al*. (2007) imaged the hypersensitive response (HR) and developing cell death induced by tobacco mosaic virus (TMV) in resistant tobacco cv. 'Samsun NN' and susceptible cv. 'Sumsun nn'. Fluorescence excitation was done using 'Xenon flash lamp (FX-4400)' in a 'Luminescence spectrometer LS52'. Observation was made 88 hrs after inoculation. UV-induced blue fluorescence increased significantly during the HR to TMV infection above 400nm when compared to the control. The difference in fluorescence gradually decreased towards the 550nm region. Infection of the susceptible tobacco cultivar 'Samsun nn' with TMV did not reveal any significant change in fluorescence emission (Chaerle *et al*., 2007).

SATELLITE REMOTE SENSING IN PLANT DISEASE DETECTION

Detecting sugarcane 'Orange rust' disease using EO-1 Hyperion hyperspectral imagery: Apan *et al*. (2004) used Hyperion satellite, EO-1 hyperspectral imagery to detect orange rust (*Puccinia kuehnii*) in sugarcane in Queensland, Australia. Forty spectral vegetation indices (SVIs) were generated from images acquired. Combination of VNIR bands with the moisture-sensitive band (1660 nm) yielded increased separability of rust affected areas. They formulated new indices, 'Disease–Water Stress Indices' (DWSI-1~R_{800}/R_{1660}; DSWI-2~R_{1660}/R_{550}; DWSI-5~(R_{800}zR_{550})/(R_{1660}zR_{680}) which produced the largest correlations, indicating their superior ability to discriminate sugarcane areas affected by orange rust disease (Apan *et al*., 2004).

MULTI-TEMPORAL REMOTE SENSING IN PLANT DISEASE DETECTION

Multi-temporal wheat disease detection by multi-spectral remote sensing: Franke and Menz (2007) evaluated high resolution QuickBird satellite multispectral multi-temporal imagery for detecting powdery mildew and leaf rust in wheat in Bonn, Germany. The data were classified using NDVI and mixture tuned matched filtering (MTMF) analysis. The classification accuracy of the first scene was 56.8%, whereas the scenes achieved considerably higher accuracies of 65.9% and 88.6% respectively (Franke and Menz, 2007).

CONCLUSION

Large scale farming of agricultural crops requires on-time detection of diseases for disease and pest management. Remote sensing provides a non-invasive, rapid, reliable, precise and accurate estimates of diseases helping in monitoring and forecasting epidemics. Hyperspectral remote sensing data taken from low altitude flights usually have high spectral and spatial resolution which can be very useful in detecting diseases in green vegetation. Multi-temporal remote sensing data have a great potential in crop disease mapping at a regional scale. Spectra based classification approach is an applicable method for crop disease identification. NDVI spectral profile between healthy and diseased crop showed large difference depicting the crop stress situation. Hence, remote sensing technology will be extremely helpful to greatly spatialize diagnostic results which in turn will render agriculture more sustainable and safe, avoiding expensive use of pesticides in crop protection. To utilise the full potential of these highly sophisticated, innovative technologies, a multi-disciplinary approach including plant pathology, engineering, and informatics is required. A robust decision support systems by trans-disciplinary cooperation will improve the acceptance and full realisation of this technique.

REFERENCES

Apan, A., Held, A., Phinn, S., Markley, J. (2004). Detecting sugarcane 'orange rust' disease using EO-1 Hyperion hyperspectral imagery. *Int. J. Remote Sens.* **25**:489-498.

Belasque, L., Gasparoto, M.C.G., Marcassa, L.G. (2008). Detection of mechanical and disease stresses in citrus plants by fluorescence spectroscopy. *Applied Optics* **47**:1922–1926.

Berdugo, C., Zito, R., Paulus, S., Mahlein, A.K. (2014). Fusion of sensor data for the detection and differentiation of plant diseases in cucumber. *Plant Pathol.* **63**:1344-1356.

Bergstrasser, S., Fanourakis, D., Schmittgen, S., Cendrero-Mateo, M. P., Jansen, M., Scharr, H., Rascher, U. (2015). HyperART: non-invasive quantification of leaf traits using hyperspectral absorption-reflectance-transmittance imaging. *Plant Methods* **11**:1.

Bock, C. H., Parker, P. E., Cook, A. Z., Gottwald, T. R. (2008). Visual rating and the use of image analysis for assessing different symptoms of citrus canker on grapefruit leaves. *Plant Dis.* **92**:530-541.

Bravo, C., Moshou, D., West, J., McCartney, A. Ramon, H. (2003). Early disease detection in wheat fields using spectral reflectance. *Biosystems Engineering* **84** (2):137–145.

Burling, K., Hunsche, M., Noga, G. (2011). Use of blue-green and chlorophyll fluorescence measurements for differentiation between nitrogen deficiency and pathogen infection in wheat. *J. Plant Physiol.* **168**:1641-1648.

Camargo, A., and Smith, J. S. (2009). Image pattern classification for the identification of disease causing agents in plants. *Comput. Electron. Agric.* **66**:121-125.

Chaerle, L., Hagenbeek, D., De Bruyne, E., Van der Straeten, D. (2007). Chlorophyll fluorescence imaging for disease-resistance screening of sugar beet. *Plant Cell Tiss. Org.* **91**:97-106.

Chaerle, L., Lenk, S., Hagenbeek, D., Buschmann, C., Straetena, D.V.D. (2007). Multicolor fluorescence imaging for early detection of the hypersensitive reaction to tobacco mosaic virus. *Journal of Plant Physiology* **164** : 253-262.

Choi, Y.H., Tapias, E.C., Kim, H.K., Lefeber, A.W.M., Erkelens, C., Verhoeven, J.T.J., Brzin, J., Zel, J., Verpoorte, R. (2004). Metabolic discrimination of *Catharanthus roseus* leaves infected by phytoplasma using 1H-NMR spectroscopy and multivariate data analysis. *Plant Physiology* **135**:2398–2410.

Colwell, R. N. (1956). Determining the prevalence of certain cereal crop diseases by means of aerial photography. *Hilgardia* **26**:223-286.

Costa, G., Noferini, M., Fiori, G., Spinelli, F. (2007). Innovative application of nondestructive techniques for fruit quality and disease diagnosis. *Acta Horticulturae* **753:**275–282.

Dakshinamurti, C., Krishnamurthy, B., Summan-war, A.S., Shanta, P., Pisharoty, P.R. (1971). Remote sensing for coconut wilt. pp. 25-29. In: *Proceedings of 6th International Symposium on Remote Sensing of Environment*. Environmental Research Institute at Michigan, Ann Arbor, U.S.A.

Das, D.K., Pradhan, S., Sehgal, V.K., Sahoo, R.N., Gupta, V.K., Singh, R. (2013). Spectral reflectance characteristics of healthy and yellow mosaic virus infected soybean (*Glycine max* L.) leaves in a semiarid environment. *Journal of Agrometeorology* **15**: 36-38.

Delalieux, S., van Aardt, J., Keulemans, W., Coppin, P. (2007). Detection of biotic stress (*Venturia inaequalis*) in apple trees using hyperspectral data: non-parametric statistical approaches and physiological implications. *Eur. J. Agron.* **27**:130-143.

Delwiche, S.R. and Kim, M.S. (2000). Hyperspectral imaging for detection of scab in wheat. Proceedings of SPIE 4203: 13–20.

Franke J. and Menz G. (2007). Multi-temporal wheat disease detection by multi-spectral remote sensing. *Precision Agriculture* **8**:161–172.

Garcia-Ruiz, F., Sankaran, S., Mari Maja, J., Lee, W.S., Rasmussen, J., Ehsani, R. (2013). Comparison of two aerial imaging platforms for identification of Huanglongbing-infected citrus trees. *Computers and Electronics in Agriculture* **91:** 106–115.

Graeff, S., Link, J., Claupein, W. (2006). Identification of powdery mildew (*Erysiphe graminis* sp. *tritici*) and take-all disease (*Gaeumannomyces graminis* sp. *tritici*) in wheat (*Triticum aestivum* L.) by means of leaf reflectance measurements. *Central European Journal of Biology* **1**: 275–288.

Huang, W., Lamb, D. W., Niu, Z., Zhang, Y., Liu, L., Wang, J. (2007). Identification of yellow rust in wheat using *in-situ* spectral reflectance measurements and airborne hyperspectral imaging. *Precis. Agric.* **8:** 187-197.

Jensen, J. R. (2000). *Remote Sensing of the Environment: An Erath Resource Perspective*, Prentice-Hall.

Konanz, S., Kocsanyi, L., Buschmann, C. (2014). Advanced multi-color fluorescence imaging system for detection of biotic and abiotic stresses in leaves. *Agriculture* **4**:79-95.

Kuska, M., Wahabzada, M., Leucker, M., Dehne, H.-W., Kersting, K., Oerke, E.-C., Steiner, U., Mahlein, A.-K. (2015). Hyperspectral phenotyping on microscopic scale – towards automated characterization of plant-pathogen interactions. *Plant Methods* **11**:28.

Lindenthal, M., Steiner, U., Dehne, H.W. and Oerke, E.C. (2005). Effect of downy mildew development on transpiration of cucumber leaves visualized by digital infrared thermography. *Phytopathology* 95(3):233-240

Mahlein, A.K. (2016). Plant disease detection by imaging sensors-Parrels and specific demands for precision agriculture and plant phenotyping. *Plant disease* **100**:241-251.

Mahlein, A.K., Oerke, E.C., Steiner, U., Dehne, H.W. (2012). Recent advances in sensing plant diseases for precision crop protection. *Eur J Plant Pathol* **133**:197–209.

Mahlein, A.K., Steiner, U., Dehne, H.-W., Oerke, E.-C. (2010). Spectral signatures of sugar beet leaves for the detection and differentiation of diseases. *Precis. Agric.* **11**:413-431.

Moshou, D., Bravo, C., Wahlen, S., West, J., McCartney, A., De Baerdemaeker, J., Ramon, H., (2006). Simultaneous identification of plant stresses and diseases in arable crops using proximal optical sensing and self-organising maps. *Precision Agriculture* **7**:149-164.

Moshou, D., Bravo, C., West, J., Wahlen, S., McCartney, A., Ramon, H. (2004). Automatic detection of 'yellow rust' in wheat using reflectance measurements and neural networks. *Comput. Electron. Agric.* **44**:173-188.

Naidu, R.A., Perry, E.M., Pierce, F.J., Mekuria, T. (2009). The potential of spectral reflectance technique for the detection of Grapevine leafroll-associated virus-3 in two red-berried wine grape cultivars. *Computers and Electronics in Agriculture* **66**:38–45.

Neumann, M., Hallau, L., Klatt, B., Kersting, K., Bauckhage, C. (2014). Erosion band features for cell phone image based plant disease classification. Pages 3315-3320 in: Proceeding of the 22nd International Conference on Pattern Recognition (ICPR), Stockholm, Sweden, 24-28 August 2014.

Oerke, E.-C., Frohling, P., Steiner, U. (2011). Thermographic assessment of scab disease on apple leaves. *Precis. Agric.* **12**:699-715.

Oerke, E.-C., Steiner, U., Dehne, H.-W., Lindenthal, M. (2006). Thermal imaging of cucumber leaves affected by downy mildew and environmental conditions. *J. Exp. Bot.* **57**:2121-2132.

Polder, G., van der Heijden, G. W. A. M., van Doorn, J., Baltissen, T. A. H. M. C. (2014). Automatic detection of tulip breaking virus (TBV) in tulip fields using machine vision. *Biosystems Eng.* **117**:35-42.

Qin, J., Burks, T.F., Kim, M.S., Chao, K., Ritenour, M.A. (2008). Citrus canker detection using hyperspectral reflectance imaging and PCA-based image classification method. *Sensing and Instrumentation for Food Quality and Safety* **2**:168–177.

Qin, J., Burks, T.F., Ritenour, M.A., Bonn, W.G. (2009). Detection of citrus canker using hyperspectral reflectance imaging with spectral information divergence. *Journal of Food Engineering* **93**:183–191.

Qin, Z. and Zhang, M. (2005). Detection of rice sheath blight for in-season disease management using multispectral remote sensing. *International Journal of Applied Earth Observation and Geoinformation* **7**:115–128.

Ray, S.S., Jain, N., Arora, R.K., Chavan, S., Panigrahy, S. (2011). Utility of hyperspectral data for potato late blight disease detection. *J Indian Soc Remote Sens* **39**:161–169.

Rousseau, C., Belin, E., Bove, E., Rousseau, D., Fabre, F., Berruyer, R., Guillaumes, J., Manceau, C., Jaques, M.-A., Boureau, T. (2013). High throughput quantitative phenotyping of plant resistance using chlorophyll fluorescence image analysis. *Plant Methods* **9**:17.

Sahoo, R.N., Ray, S.S., Manjunath, K.R. (2015). Hyperspectral remote sensing of agriculture. *Current Science* **108**:848-859.

Sankaran, S., Mishra, A., Ehsani, R., Davis, C. (2010). A review of advanced techniques for detecting plant diseases. *Computers and Electronics in Agriculture* **72**: 1–13.

Shafri, H.Z.M. and Hamdan, N. (2009). Hyperspectral imagery for mapping disease infection in oil palm plantation using vegetation indices and red edge techniques. *American Journal of Applied Sciences* **6**: 1031-1035.

Sighicelli, M., Colao, F., Lai, A., Patsaeva, S. (2009). Monitoring post-harvest orange fruit disease by fluorescence and reflectance hyperspectral imaging. *ISHS Acta Horticulturae* **817**:277–284.

Wang, X., Zhang, M., Zhu, J., Geng, S. (2008). Spectral prediction of Phytophthora infestans infection on tomatoes using artificial neural network (ANN). *Int. J. Remote Sens.* **29**:1693-1706.

Zhang, M., Qin, Z., Liu, X. (2005). Remote sensed spectral imagery to detect late blight in field tomatoes. *Precision Agriculture* **6** :489–508.