

Plant Disease Detection by Sensors and its Demands for Precision Agriculture

***Rovidha S. Rasool¹, Aqleema Banoo², Taibah Bashir³, Rabia Latif⁴**

^{1,2,3,4}Division of Plant Pathology

Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir,
Shalimar, Srinagar (J&K), (India)

ABSTRACT

Precision agriculture or site-specific management has been defined as a knowledge-based technical management system that can help optimize farm profits and minimize agriculture's impact on the environment. Fungal pathogens cause serious losses to yields and quality of agricultural crops globally. Early and accurate detection and diagnosis of plant diseases are key factors in plant production and the reduction of both qualitative and quantitative losses in crop yield. Early detection of plant disease in the field can allow producers to rapidly treat affected areas and to more accurately predict yield losses. Conventional methods of detection rely on scouting and visual examination and often result in detection after the optimum time for control has passed. In addition to preventing individual producer losses, early detection will allow for the prevention of spread to neighboring fields or crops. Using diagnostic symptoms of pathogens such as changes in leaf pigments, leaf structure and moisture content, hyperspectral and multispectral imaging can aid in mapping fields for plant disease management. Optical techniques, such as RGB imaging, multi- and hyperspectral sensors, thermography, or chlorophyll fluorescence, have proven their potential in automated, objective, and reproducible detection systems for the identification and quantification of plant diseases at early time points in epidemics. Recently, 3D scanning has also been added as an optical analysis that supplies additional information on crop plant vitality. Different platforms from proximal to remote sensing are available for multiscale monitoring of single crop organs or entire fields. The most relevant areas of application of sensor-based analyses are precision agriculture and plant phenotyping.

Keywords: disease, detection, epidemic, precision, phenotyping, sensors

I.INTRODUCTION

Agriculture is a broad and promising area demanding technological solutions with the aim of increasing production or accurate inventories for sustainability while the environmental impact is minimized by reducing the application of agro-chemicals and increasing the use of environmental friendly agronomical practices. In addition to this there are different technologies that are used for increasing the production (Wilson, 2013). There are Sensors-based technologies that provide appropriate tools to achieve the above mentioned goals. The advances in explosive technological and development in recent years enormously facilitates the attainment of

these objectives removing many barriers for their implementation, including the reservations expressed by the farmers themselves (Aroca *et al.*, 2013). Precision Agriculture is an emerging area where sensor-based technologies play an important role. Sensors are designed according to the problems to be solved or needs identified by farmers. Another important contribution to precision agriculture is the development of mathematical tools that allow monitoring and classification of plants and fruits by the severity of the disease (Hahn, 2009), based on advanced statistical methods, as reviewed by Mulla (2013) and Behmann *et al.*, (2015). These mathematical tools could be used as classifiers, identifying stressed plants, or monitoring the evolution of pathogens. This strategy can also be applied on plant phenotyping programs (Fiorani and Schurr, 2013). Classifiers are used as models and these models are able to identify what category new data belong to, thus classifying them accurately. Machine learning includes a wide range of classifiers, such as ANN and LRA. ANN is a network inspired by biological neural networks that learn from input and output data (Hill *et al.*, 1994). On the other hand, LRA is a statistical method that estimates the probability of a dichotomous outcome (“healthy” vs. “infected”) based on one or more independent variables. For this reason, LRA is of particular interest and widely used in biomedicine (Hosmer *et al.*, 2013). Independently from the model used, part of the dataset obtained by experimental measurements is used for training the model, and the remaining part is used for its validation. The goodness of the model is provided by the parameters sensitivity, specificity, and accuracy. The proportion of samples predicted to be infected that are actually “infected” is referred to as sensitivity or true positive rate, while the proportion of samples that are correctly predicted to be “healthy” is called specificity, or true negative rate. Accuracy is the proportion of right guesses, both “healthy” and “infected” samples (Parikh *et al.*, 2008).

Both precision agriculture and plant phenotyping have specific needs and challenges in regards to plant disease detection. In order to obtain objective and reliable automated diagnosis and detection of plant diseases, new approaches must be introduced and incorporated into traditional monitoring and rating systems. Optical sensors are promising tools for non invasive disease detection and diagnosis. There are an increasing number of imaging and non invasive sensors available that can support diagnosis and plant disease detection. The progress in sensor and information technologies together with the expansion of geographic information systems opens new opportunities for precision agriculture and plant phenotyping.

1.1 Role of Sensors for plant disease detection:

RGB-imaging

Digital photographic images are important tools in plant pathology for assessing plant health. Digital cameras are easy to handle and are a simple source of RGB (red, green, and blue) digital images for disease detection, identification, and quantification. The technical parameters of these simple, handheld devices such as the light sensitivity of the photo sensor, spatial resolution, or optical and digital focus have improved significantly every year. Today, nearly every person, farmer or phytopathologist, carries modern and sophisticated digital camera sensors together with a mobile phone or tablet computer. Video cameras or scanners are alternative methods for

assessing digital images of different plant organs, from roots to inflorescences. RGB sensors are used on every scale of resolution for monitoring plants during the growing season.

RGB-color images with the red, green, and blue channels have been used to detect biotic stress in plants (Bock *et al.*, 2008). Along with color information in the RGB, LAB (L for lightness and A and B for the color-opponent dimensions, based on nonlinearly compressed coordinates), YCBCR (color compression scheme Y is the luma component and CB and CR are the blue-difference and red-difference chroma components, respectively), or HSV (hue, saturation, value) color space, the spatial information provides important characteristics of plant diseases (Bock *et al.*, 2010). Furthermore, color, gray levels, texture, dispersion, connectivity, and shape parameters can be defined as features for the detection and identification of disease symptoms in plants (Camargo and Smith 2009; Neumann *et al.*, 2014). Several research groups have used pattern recognition methods and machine learning to detect and to identify plant diseases from RGB images. In addition, systematic selection of relevant features from the RGB images increase classification accuracies (Behmann *et al.*, 2014). Digital image analysis is a well-established technology used in plant disease assessment. Several software packages, such as ASSESS 2.0, "Leaf Doctor," Scion Image software, and custom-made modules are available (Bock *et al.*, 2010; Pethybridge and Nelson 2015; Tucker and Chakraborty 1997; Wijekoon *et al.*, 2008). In ASSESS 2.0, the color distribution of the images is analyzed in histograms, which are the basis for subsequent thresholding. The parameters for healthy and diseased areas can be adjusted by the user in a well-organized graphical user interface. In addition, disease severity can be extracted as diseased pixels or as a percentage after the background is masked from the object of interest. ASSESS 2.0 is very practical for the evaluation of disease severity on single leaves and well-arranged images. Special attention must be given to the image acquisition step. Uniform focus, sharpness, and illumination are crucial for high accuracy and reliable results from automated image analysis. Furthermore, under natural conditions, the imaging angle (leaf orientation) and distance between the object and the sensor (pixel size) are additional influences on the image quality. Difficulty in detection and low levels of accuracy are often the result of heterogenic conditions and low image quality. The most important principle for success is a sound standardized imaging procedure that yields repeatable results.

Multi- and hyperspectral reflectance sensors.

Spectral sensors are generally categorized based on the spectral resolution (i.e., the number and width of measured wavebands), on their spatial scale, and on the type of detector, (i.e., imaging or nonimaging sensor systems). Multispectral sensors were the first spectral sensors invented. These sensors typically assess the spectral information of objects in several relatively broad wavebands. Multispectral imaging cameras may provide data, for instance, in the R, G, and B wavebands and in an additional near-infrared band. The evolution of modern hyperspectral sensors increased the complexity of the measured data by a spectral range of up to 350 to 2,500 nm and a possible narrow spectral resolution below 1 nm (Steiner *et al.*, 2008). Contrary to nonimaging sensors, which average the spectral information over a certain area, hyperspectral imaging sensors provide

spectral and spatial information for the imaged object. Hyperspectral data can be observed as huge matrices with spatial x- and y-axes, and the spectral information as reflectance intensity per waveband in the third dimension, z. The spatial resolution strongly depends on the distance between the sensor and the object. Thus, airborne or space borne, far range systems have lower spatial resolution than near-range or microscopic systems. The spatial resolution has a strong influence on the detection of plant diseases or plant-pathogen interactions (Mahlein *et al.*, 2012b; West *et al.*, 2003). Airborne sensors are suitable for the detection of field patches that are diseased with soil borne pathogens (Hillnhütter *et al.*, 2011) or in later stages of the diseases (Mahlein *et al.*, 2012a; Mewes *et al.*, 2011; Steddom *et al.*, 2005). Sensors with a spatial resolution of approximately 1 m are hardly suitable for the detection of single symptoms or diseased leaves and plants; here, proximal sensor platforms are preferable (Oerke *et al.*, 2014; West *et al.*, 2003). Despite multiple studies the use of innovative hyperspectral imaging systems in plant pathology and in disease severity assessment is still in the research stage (Bock *et al.*, 2010). The optical properties of leaves are characterized by (i) light transmission through a leaf, (ii) light that is absorbed by leaf chemicals (e.g., pigments, water, sugars, lignin, and amino acids), and (iii) light reflected from internal leaf structures or directly reflected from the leaf surface. Thus, reflectance of light from plants is a complex phenomenon dependent on multiple biophysical and biochemical interactions. The visible range (VIS 400 to 700 nm) is mainly influenced by leaf pigment content, the near-infrared reflectance (NIR 700 to 1,100 nm) depends on the leaf structure, internal scattering processes, and on the absorption by leaf water, and the short-wave infrared (1,100 to 2,500 nm) is influenced by the composition of leaf chemicals and water (Carter and Knapp 2001; Jacquemoud and Ustin 2001). Changes in reflectance due to plant pathogens and plant diseases can be explained by impairments in the leaf structure and chemical composition of the tissue during pathogenesis that is highly specific, e.g., succession of chlorotic and necrotic tissue or the appearance of typical fungal structures, such as powdery mildew hyphae and conidia or rust uredospores. Whereas biotrophic fungi such as powdery mildews or rusts have a relatively low impact on tissue structure and chlorophyll composition during early infection perthotrophic pathogens, such as those that cause leaf spots, often induce degradation of tissue due to pathogen-specific toxins or enzymes that ultimately results in necrotic lesions. In contrast, powdery mildews and rust fungi produce fungal structures on the leaf surface that can influence the optical properties of the plant-pathogen interaction. Complex and unique interactions are exemplarily visualized for sugar beet leaf diseases by raster electron microscopy and by semithin sections of diseased leaf parts. These highly complex and unique disease patterns enable an identification of diseases based on the spectral properties of plants Mahlein *et al.*, (2010, 2013) demonstrated the differentiation of foliar pathogens of sugar beet based on leaf reflectance. Building on these results, Rumpf *et al.*, (2010) was able to detect early *Cercospora* leaf spot, powdery mildew, and rust-diseased sugar beets before the appearance of visible symptoms. In other plant pathogen systems, noninvasive spectral data proved to be useful for the monitoring of *Fusarium graminearum* in wheat (Bauriegel *et al.*, 2011), *Venturia inaequalis* in apple (Delalieux *et al.*, 2007), or *Phytophthora infestans* in tomato (Wang *et al.*, 2008). In proximal sensing, hyperspectral imaging also was shown to be useful for the assessment of mycotoxin-producing pathogens in maize (Del Fiore *et al.*, 2010). Furthermore, Bravo *et al.*, (2003) used in-field spectral images for the early detection of yellow rust infected wheat. Soil borne diseases were successfully discriminated by Hillnhütter *et al.*, (2011), who looked at the

symptoms caused by the nematode *Heterodera schachtii* and the soil borne fungus *Rhizoctonia solani* in sugar beet fields. In work on sugarcane, Apan *et al.*, (2004) were able to detect orange rust using EO-1 Hyperion hyperspectral imaging. Later, Huang *et al.*, (2007) obtained reliable and accurate detection of yellow rust in wheat by ground based spectral measurements and airborne hyperspectral imaging. In addition to detection of plant diseases during the vegetation period, hyperspectral imaging is widely used for monitoring fruit health and quality. Canker lesions of citrus fruits (Qin *et al.*, 2009), apple surface defects (Mehl *et al.*, 2004), or rot of strawberries (ElMasry *et al.*, 2007) can be identified by hyperspectral imaging sensors. These techniques are important in screening fruits and crops to avoid storage diseases.

Thermal sensors

Infrared thermography (IRT) assesses plant temperature and is correlated with plant water status (Jones *et al.*, 2002), the microclimate in crop stands (Lenthe *et al.*, 2007), and with changes in transpiration due to early infections by plant pathogens (Oerke *et al.*, 2006). Emitted infrared radiation in the thermal infrared range from 8 to 12 μm can be detected by thermographic and infrared cameras and is illustrated in false color images, where each image pixel contains the temperature value of the measured object. In plant science, IRT can be used at different temporal and spatial scales from airborne to small scale applications. However, it is often subject to environmental factors such as ambient temperature, sunlight, rainfall, or wind speed. The leaf temperature shows a close correlation to the plant transpiration (Jones 1992; Jones *et al.*, 2002), which is affected by a diversity of pathogens in different ways. Whereas many foliar pathogens, such as leaf spots or rusts, induce local and well-defined changes, impairment by root pathogens (e.g., *Rhizoctonia solani* or *Pythium* spp.) or systemic infections (e.g., *Fusarium* spp.) often influences the transpiration rate and the water flow of the entire plant or plant organs. Local temperature changes due to pathogen infection or to defense mechanisms have been reported for plant-virus interactions in tobacco and for *Cercospora beticola* in sugar beet by Chaerle *et al.*, (2004). Oerke *et al.*, (2006) monitored cucumber diseased with downy mildew (*Pseudoperonospora cubensis*) or scab disease in apple caused by *Venturia inaequalis* (Oerke *et al.*, 2011) successfully by IRT. In the plant-pathosystem for apple and *V. inaequalis*, thermography was also able to visualize the spatial colonization of apple tissues by the pathogen over and beyond visible symptoms, where hyphae and conidia were only microscopically detectable (Oerke *et al.*, 2011). Gomez (2014) monitored the infection and spread of *Peronospora sparsa* on different *Rosa* cultivars. Applications in the field have been demonstrated by Nilsson (1991), with a high correlation between disease severity of various root and leaf diseases and in different crops (barley, wheat, oat, sugar beet, potatoes, etc.). For effective analysis of IRT images, the heterogeneity between and within leaves can be utilized. The mean temperature difference within single leaves, plants, and crop stands is an important indicator for the appearance of plant disease.

1.2. Precision agriculture for managing plant diseases:

Plant pathogens are severe constraints to the production yield of crop fields worldwide. Current agricultural policies are aimed to minimize the use of pesticides and fertilizers through better targeting, and the integration with cultural control of weeds, pests, and diseases (Maloy, 2005). The implementation of precision agriculture relies on the development of technologies that allow the identification and mapping of constraints in the crop fields, such as imaging techniques (Mulla, 2013). They can be used to evaluate the effects of stress on plant metabolism (Cerovic *et al.*, 1999; Barón *et al.*, 2012, 2016). Consequently, imaging techniques are powerful non-destructive tools that have become essential: they provide crucial information for the decision-making and for the right timing of the procedures to be applied (Usha and Singh, 2013; Li *et al.*, 2014; Mahlein, 2016).

Disease and Pathogen Detection During plant-pathogen infection, the physiological state of the infected tissue is altered, such as changes in photosynthesis, transpiration, stomatal conductance, accumulation of Salicylic acid (SA) and even cell death (Xu *et al.*, 2006). Foliar disease can directly be detected by modern optical sensor technology. Using hyperspectral reflectance images (Olivier *et al.*, 2003) and (Moshou *et al.*, 2004) were able to identify powdery mildew of barley, diseased cucumber leaves and yellow rust of wheat respectively. But digital infrared thermography have the potential to identify and quantify with high spatial resolution management zones in disease control and associated pathogens, as they are sensitive to physiological disorders associated with fungal attack as well as disease (Oerke *et al.*, 2006), in addition leaf diseases often affect plant transpiration. Thermal infrared has been proved by various researchers to be a useful tool for the pre-symptomatic effect of disease and pathogen on plant. (Oerke *et al.*, 2006) (Oerke *et al.*, 2005) used thermal infrared to detect *Pseudoperonospora cubensis* that causes downy mildew in cucumber, The maximum temperature difference (MTD) within a leaf or a canopy turned out to be suitable for the differentiation of infected and non-infected tissue under controlled conditions, transpiration rate and leaf temperature were similar for healthy and infected leaves under non controlled conditions but for infected tissues, transpiration rates showed higher variation depending on disease symptoms. However, (Xu *et al.*, 2006) found a decrease in leaf temperature of about 0.5°C - 1.3°C lower for the infected leaves than the healthy leaves while they were assessing the different temperature distribution between the leaves infected by tobacco mosaic virus strain-TMV-U1 and the non-infected leaves within different tomato species using digital infrared thermal imaging in combination with microscopic observations. However in the later stages of the disease, the MTD decreased because of leaf senescence and leaf transpiration was increased by all stages of scab development, therefore, MTD may be used not only for the differentiation between diseased and non-diseased leaves, but also for disease quantification. TIR could also be used to detect pathogen before visible symptoms occur (Stoll *et al.*, 2008) explored the potential of thermal imaging for pathogen detection (*Plasmopara viticola*) in grapevine (*Vitis vinifera* L. cv. Riesling) on well irrigated or non-irrigated grapevines. The analysis of thermal images showed that pathogen development caused an increase in leaf temperature at the point of infection in irrigated vines, non-irrigated vines showed a lower temperature at the sites of inoculation. Thermal imaging is a straightforward choice for providing information for pre-symptomatic diagnosis of biotic stresses before the appearance of visible necrosis on leaves by visualizing and analyzing the temperature difference between infected and non-infected leaves (Kim *et al.*, 2014).

1.3. Remote sensing of plant disease:

Remote sensing is a technique for obtaining information on an object without physical contact, by measuring the electromagnetic energy reflected/backscattered or emitted by the surface of the Earth (De Jong and Van der Meer 2006). Being noncontact technique, spectral measurements is included in remote sensing that acquired by portable instruments such as handheld spectroradiometers (also called proximal sensing). These measurements are processed and analyzed to retrieve information on the object observed (i.e., plant health, in this case). It is an indirect assessment technique, able to monitor vegetation conditions from distance, and evaluate the spatial extent and patterns of vegetation characteristics and plant health, in this application. Sensors can be distinguished into active or passive whether they emit artificial radiation and measure the energy reflected or backscattered (active sensors) or they measure the reflected solar radiation or the emitted thermal radiation (passive sensors). Radar and Lidar are examples of active RS instruments. The use of passive instruments can measure the solar radiation reflected in the visible (VIS; wavelength range, 400– 700 nm), near-infrared (NIR; wavelength range, 700– 1,100 nm), and shortwave infrared (SWIR; 1,100– 2,500 nm), and the energy emitted in the thermal infrared (TIR; 3 to 15 μ m) wavelength regions of the electromagnetic spectrum. Passive instruments, for their specific characteristics, are employed in the vast majority of RS PDD applications (Heald *et al.*, 1972). The spectral signature of vegetation is influenced by variables describing canopy structure (leaf area and orientation, spatial arrangement, and roughness) and on the optical, dielectric, or thermal characteristics of the vegetation elements.

There are certain examples in which ARS employed remote sensing technology for detecting crop disease and assessing its impact on productivity include using CIR photography to identify circular areas affected by cotton root rot, *Phymatotrichum omnivorum*; (Henneberry *et al.*, 1979) and to estimate yield losses caused by blackroot disease in sugar beets (Schneider and Safir, 1975). Cook *et al.* (1999) also demonstrated the potential for aerial video imagery to detect *P. omnivorum* in kenaf, a crop whose tall growth habit makes it almost impossible to survey from the ground. The TIR can provide previsual, detection of diseases that interfere with the flow of water from the soil through the plant to the atmosphere. As an example, Pinter *et al.* (1979) found that cotton plants whose roots were infected with the soil-borne fungus *P. omnivorum* and sugar beets infected with *Pythium aphanidermatum* both displayed sunlit leaf temperatures that were 3 to 5°C warmer than adjacent healthy plants. The TIR was also useful for detecting root disease in red clover under irrigated conditions (Oliva *et al.*, 1994a). Much more research is required when using remote sensing for identifying specific diseases or when separating them from other causes of plant stress. Hyperspectral techniques are likely to provide some assistance, but coupling existing techniques with weather driven computer models of disease development will probably provide the best approach.

II.CONCLUSION

Early detection of pathogen infections is pivotal to managing polycyclic diseases. The detection of plant diseases was done by traditional nucleic acid and serological assays but, nowadays other innovative methods like remote sensing, use of various sensors and application of precision agriculture are used for quick and

efficient detection and diagnosis of diseases. Many aspects of crop management have already begun to benefit from application of remote sensing and other technologies. The future brings tremendous prospectus for integrating the spatially and temporally rich information provided through these innovative technologies.

REFERENCES

- [1.] Apan, A., Held, A., Phinn, S. and Markley, J. 2004. Detecting sugarcane ‘orange rust’ disease using EO-1 Hyperion hyperspectral imagery. *International Journal of Remote Sensing* **25**:489-498.
- [2.] Aroca, R.V., Gomes, R.B., Dantas, R.R., Calbo, A.G. and Gonçalves, L.M.G. 2013. A Wearable Mobile Sensor Platform to Assist Fruit Grading. *Sensors* **13**: 6109–6140.
- [3.] Baron, M., Flexas, J., Delucia, E. H. 2012. “Photosynthetic responses to biotic stress,” in *Terrestrial Photosynthesis in a Changing Environment: A Molecular, Physiological, and Ecological Approach* 331–350.
- [4.] Baron, M., Pineda, M. and Perez-Bueno M. L. 2016. Picturing pathogen infection in plants. *Z. Naturforsch. C* **71**: 355–368.
- [5.] Bauriegel, E., Giebel, A., Geyer, M., Schmidt, U. and Herppich, W. B. 2011. Early detection of *Fusarium* infection in wheat using hyper-spectral imaging. *Computers and Electronics in Agriculture* **75**:304-312.
- [6.] Behmann, J., Mahlein, A.K., Rumpf, T., Romer, C. and Plumer, L. 2015. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. *Precision Agriculture* **16**: 239–260.
- [7.] Behmann, J., Mahlein, A.-K., Rumpf, T., Romer, C. and Plumer, L. 2014. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. *Precision Agriculture* **16**: 239-260.
- [8.] Bock, C. H., Parker, P. E., Cook, A. Z. and Gottwald, T. R. 2008. Visual rating and the use of image analysis for assessing different symptoms of citrus canker on grapefruit leaves. *Plant Diseases* **92**:530-541.
- [9.] Bock, C. H., Poole, G. H., Parker, P. E. and Gottwald, T. R. 2010. Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Science* **29**:59.
- [10.] Bravo, C., Moshou, D., West, J., McCartney, A. and Ramon, H. 2003. Early disease detection in wheat fields using spectral reflectance. *Biosystems Engineering* **84**:137-145.
- [11.] Camargo, A. and Smith, J. S. 2009. Image pattern classification for the identification of disease causing agents in plants. *Computers and Electronics in Agriculture* **66**:121-125.

- [12.] Carter, G. A. and Knapp, A. K. 2001. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. *American Journal of Botany* **88**:677-684.
- [13.] Cerovic, Z. G., Samson G., Morales F., Tremblay N. and Moya I. 1999. Ultraviolet-induced fluorescence for plant monitoring: present state and prospects. *Agronomie* **19**: 543–578.
- [14.] Chaerle, L., Hagenbeek, D., De Bruyne, E., Valcke, R. and Straeten, D. 2004. Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. *Plant Cell Physiology* **45**: 887-896.
- [15.] Cook, C.G., Escobar, D.E., Everitt, J.H., Cavazos, I., Robinson, A.F. and Davis, M.R. 1999. Utilizing airborne video imagery in kenaf management and production. *Industrial Crops and Products* **9**: 205–210.
- [16.] De Jong S. and van der Meer, F.D. 2006. Remote sensing image analysis: including the spatial domain. Springer editions, Dordrecht.
- [17.] Del Fiore, A., Reverberri, M., Ricelli, A., Pinzari, F., Serranti, S., Fabbri, A. A., Bonifazi, G. and Fanelli, C. 2010. Early detection of toxigenic fungi on maize by hyperspectral imaging analysis. *International Journal of Food Microbiology* **144**:64-71.
- [18.] Delalieux, S., van Aardt, J., Keulemans, W. and Coppin, P. 2007. Detection of biotic stress (*Venturia inaequalis*) in apple trees using hyperspectral data: non-parametric statistical approaches and physiological implications. *European Journal of Agronomy* **27**:130-143.
- [19.] ElMasry, G., Wang, N., ElSayed, A. and Ngadi, M. 2007. Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. *Journal of Food Engineering* **81**: 98-107.
- [20.] Fiorani, F. and Schurr, U. 2013. Future scenarios for plant phenotyping. *Annual Review of Plant Biology* **64**: 267–291.
- [21.] Gomez, S. 2014. Infection and spread of *Peronospora sparsa* on *Rosa* sp. (Berk.) - a microscopic and a thermographic approach. Dissertation, University of Bonn, Germany.
- [22.] Hahn, F. 2009. Actual pathogen detection: sensors and algorithms- A review. *Algorithms* **2**: 301–338.
- [23.] Heald, C.M., W.J. Thames, and C.L. Wiegand. 1972. Detection of *Rotylenchulus reniformis* infestations by aerial infrared photography. *Journal of Nematology* **4**:299–300.
- [24.] Henneberry, T.J., W.G. Hart, L.A. Bariola, D.L. Kittock, H.F. Arle, M.R. Davis, and S.J. Ingle. 1979. Parameters of cotton cultivation from infrared aerial photography. *Photogrammetric Engineering & Remote Sensing* **45**: 1129–1133.
- [25.] Hill, T., Marquez L. and Remus W. 1994. Artificial neural network models for forecasting and decision making. *International Journal of Forecasting* **10**: 5–15.

- [26.] Hillnhutter, C., Mahlein, A.K., Sikora, R. A., and Oerke, E.C. 2011. Remote sensing to detect plant stress induced by *Heterodera schachtii* and *Rhizoctonia solani* in sugar beet fields. *Field Crops Research* **122**:70-77.
- [27.] Hillnhutter, C., Schweizer, A., Kuhnhold, V., and Sikora, R. A. 2010. Remote sensing for the detection of soil-borne plant parasitic nematodes and fungal pathogens. Precision crop protection eds. Springer 151-165.
- [28.] Hosmer, J., David, W., Lemeshow, S. and Sturdivant R. X. 2013. *Applied Logistic Regression*, 3rd Edition. Hoboken, NJ: Jon Wiley & Sons, Inc.
- [29.] Huang, W., Lamb, D. W., Niu, Z., Zhang, Y., Liu, L., and Wang, J. 2007. Identification of yellow rust in wheat using in-situ spectral reflectance measurements and airborne hyperspectral imaging. *Precision Agriculture* **8**:187-197.
- [30.] Jacquemoud, S. and Ustin, S. L. 2001. Leaf optical properties: a state of the art. Pages 223-232 in: Proceedings of the 8th International Symposium Physical Measurements & Signatures in Remote Sensing, 8–12 January 2001, CNES, Aussois, France.
- [31.] Jones, H. G. 1992. Plant and microclimate, 2nd ed. Cambridge University Press, Cambridge, UK.
- [32.] Jones, H. G., Stoll, M., Santosa, T., de Sousa, C., Chaves, M. M. and Grant, O. M. 2002. Use of infrared thermography for monitoring stomatal closure in the field: Application to grapevine. *Journal of Experimental Botany* **53**: 2249-2260.
- [33.] Kim, G., Kim, G.-H., Park, J., Kim, D.Y. and Cho, B.-K. 2014. Application of Infrared Lock-In Thermography for the Quantitative Evaluation of Bruises on Pears. *Infrared Physics & Technology* **63**: 133-139.
- [34.] Lenthe, J.H., Oerke, E.C. and Dehne, H.W. 2007. Digital infrared thermography for monitoring canopy health of wheat. *Precision Agriculture* **8**:15-26.
- [35.] Li L., Zhang Q., Huang D. 2014. A review of imaging techniques for plant phenotyping. *Sensors* **14**: 20078–20111.
- [36.] Mahlein, A.K. 2016. Plant disease detection by imaging sensors – parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease* **100**: 241–251.
- [37.] Mahlein, A.K., Oerke, E.C., Steiner, U. and Dehne, H.W. 2012a. Recent advances in sensing plant diseases for precision crop protection. *European Journal of Plant Pathology* **133**:197-209.
- [38.] Mahlein, A.K., Rumpf, T., Welke, P., Dehne, H.-W., Plumer, L., Steiner, U., and Oerke, E.C. 2013. Development of spectral vegetation indices for detecting and identifying plant diseases. *Remote Sensing of Environment* **128**:21-30.

- [39.] Mahlein, A.K., Steiner, U., Dehne, H.W. and Oerke, E.C. 2010. Spectral signatures of sugar beet leaves for the detection and differentiation of diseases. *Precision Agriculture* **11**:413-431.
- [40.] Mahlein, A.K., Steiner, U., Hillnhutter, C., Dehne, H.W. and Oerke, E.C. 2012b. Hyperspectral imaging for small-scale analysis of symptoms caused by different sugar beet disease. *Plant Methods* **8**:3
- [41.] Maloy O. C. 2005. Plant disease management. *Plant Health Instructor* **10**: 0202-01.
- [42.] Mehl, P. M., Chen, Y.-R., Kim, S. M. and Chan, D. E. 2004. Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations *Journal of Food Engineering* **61**:67-81.
- [43.] Mewes, T., Franke, J. and Menz, G. 2011. Spectral requirements on airborne hyperspectral remote sensing data for wheat disease detection. *Precision Agriculture* **12**:795-812.
- [44.] Moshou, D., Bravo, C., West, J., Wahlen, S., McCann, A. and Ramon, H. 2004. Automatic Detection of Yellow Rust in Wheat Using Reflectance Measurements and Neural Networks. *Computers and Electronics in Agriculture* **44**: 173-188.
- [45.] Mulla D. J. 2013. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. *Biosystems Engineering* **114**: 358–371.
- [46.] Neumann, M., Hallau, L., Klatt, B., Kersting, K. and 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.
- [47.] Nilsson, H. E. 1991. Hand-held radiometry and IR-thermography of plant diseases in field plot experiments. *International Journal of Remote Sensing* **12**:545-557.
- [48.] Oerke, E.-C., Lindenthal, M., Fröhling, P. and Steiner, U. 2005. Digital Infrared Thermography for the Assessment of Leaf Pathogens. *The 5th European Conference on Precision Agriculture*, Uppsala, 9-12 June 2005, 91-98.
- [49.] Oerke, E.C., Steiner, U., Dehne, H.W. and Lindenthal, M. 2006. Thermal Imaging of Cucumber Leaves Affected by Downy Mildew and Environmental Conditions. *Experimental Botany* **57**: 2121-2132.
- [50.] Oerke, E.C., Fröhling, P., and Steiner, U. 2011. Thermographic assessment of scab disease on apple leaves. *Precision Agriculture* **12**:699-715.
- [51.] Oerke E.C., Mahlein A.-K., Steiner U. 2014. "Proximal sensing of plant diseases," in *Detection and Diagnostics of Plant Pathogens*, eds Gullino M. L., Bonants P. J. M., editors. (Dordrecht: Springer), 55–68.
- [52.] Oliva, R.N., J.J. Steiner, and W.C. Young. 1994a. Red-clover seed production: I. Crop water requirements and irrigation timing, *Crop Science* **34**:178–184.

- [53.] Olivier, M., Heming, S. and Adams, G.G. 2003. Exploring the Spatial Variation of Take-All (*Gaeumannomyces graminis* var. *tritici*) for Site-Specific Management. In: *4th European Conference on Precision Agriculture*, Wageningen Academic Publishers, Berlin, 481-486.
- [54.] Parikh, R., Mathai, A., Parikh, S., Chandra Sekhar G. and Thomas R. 2008. Understanding and using sensitivity, specificity and predictive values. *Indian Journal of Ophthalmology* **56**: 45–50.
- [55.] Pethybridge, S. J. and Nelson, S. C. 2015. Leaf doctor: a new portable application for quantifying plant disease severity. *Plant Disease* **99**:1310-1316.
- [56.] Pinter, P.J., Hatfield, J.L., Schepers, J. S., Barnes, E.M., Moran, M.S., Daughtry, C.S.T. and Upchurch, D. R. 2003. Remote sensing for crop management. *Photogrammetric Engineering & Remote Sensing* **69**: 647-664.
- [57.] Qin, J., Burks, T. F., Ritenour, M. A., and Bonn, W. G. 2009. Detection of citrus canker using hyperspectral reflectance imaging with spectral information divergence. *Journal of Food Engineering* **93**:183-191.
- [58.] Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W. and Plumer, L. 2010. Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance. *Computers and Electronics in Agriculture* **74**:91-99.
- [59.] Schneider, C.L. and Safir, G.R. 1975. Infrared aerial photography estimation of yield potential in sugarbeets exposed to blackrot disease. *Plant Disease Reporter* **59**: 627–631.
- [60.] Steddom, K., Bredehoeft, M. W., Khan, M. and Rush, C. M. 2005. Comparison of visual and multispectral radiometric disease evaluations of *Cercospora* leaf spot of sugar beet. *Plant Disease* **89**:153-158.
- [61.] Stoll, M., Schultz, H.R. and Loehnertz, B.B. 2008. Exploring the Sensitivity of Thermal Imaging for *Plasmopara viticola* Pathogen Detection in Grapevines under Different Water Status. *Functional Plant Biology* **35**: 281-288.
- [62.] Tucker, C. C. and Chakraborty, S. 1997. Quantitative assessment of lesion characteristic and disease severity using digital image processing. *Journal of Phytopathology* **145**:273-278.
- [63.] Usha K. and Singh B. 2013. Potential applications of remote sensing in horticulture – A review. *Scientia Horticulturae* **153**: 71–83.
- [64.] Wang, X., Zhang, M., Zhu, J. and Geng, S. 2008. Spectral prediction of *Phytophthora infestans* infection on tomatoes using artificial neural network (ANN). *International Journal of Remote Sensing* **29**:1693-1706.
- [65.] West, J. S., Bravo, C., Oberti, R., Lemaire, D., Moshou, D. and McCartney, H. A. 2003. The potential of optical canopy measurement for targeted control of field crop diseases. *Annual Review of Phytopathology* **41**:593-614.

- [66.] Wijekoon, C. P., Goodwin, P. H., and Hsiang, T. 2008. Quantifying fungal infection of plant leaves by digital image analysis using Scion Image software. *Journal of Microbiological Methods* **74**:94-101.
- [67.] Wilson A.D. 2013. Diverse Applications of Electronic-Nose Technologies in Agriculture and Forestry. *Sensors* **13**:2295–2348.
- [68.] Xu, H., Zhu, S., Ying, Y. and Jiang, H. 2006. Early Detection of Plant Disease Using Infrared Thermal Imaging. *Proceedings of Optics for Natural Resources, Agriculture, and Foods*, **6381**, 638110.