

# Aiming at decision making in plant disease protection and phenotyping by the use of optical sensors

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**Abstract** Protection of crops against plant diseases is crucial in crop production. Agricultural practice and scientific research is confronted with new challenges. Environmentally friendly and sustainable solutions are increasingly demanded. Therefore, the precise detection of primary infection sites and disease dynamics is fundamental to make a decision for a subsequent management practice. In this context, optical sensors can provide an accurate and objective detection of plant diseases. This has awoken the interest and expectation from the public, farmers, and companies for sophisticated optical sensors in agriculture, providing promising solutions. Nevertheless, the application of optical sensors in a practical context in the field is still challenging, and sophisticated data analysis methods have to be developed. In general, the entire system pipeline, consisting of the type of sensor, the platform carrying the sensor, and the decision making process by data analysis has to be tailored to the specific problem. Here, we briefly recount the possibilities and challenges using optical sensors in research and practice for plant disease protection. Optical sensor-based approaches are considered as

a key element in plant phenotyping. This overview addresses mainly hyperspectral imaging as it determines several plant parameters that represent the basis for more specific sensors in the future.

**Keywords** Hyperspectral imaging · Precision agriculture · Plant phenotyping

## Introduction

Recent cultivation techniques have resulted in higher plant pathogen incidence and susceptibility of plants in agriculture (Bebber et al. 2014). Besides the import of new diseases by human activities and favorable conditions due to climate changes, factors that increase the infestation rate of fungal pathogens on plants are the use of non-locally adapted high-yield varieties, unbalanced fertilization, reduced crop rotation, and tillage cultivation (Bebber et al. 2014). Plant pathogens reduce the quality and quantity of products from crop plants and increase costs in agriculture due to the application of plant protection measures. Plant disease management strategies should be based on a precise diagnosis and documentation of the disease appearance and incidence within crop stands. Plant diseases often exhibit a heterogeneous distribution within crop stands and are highly dynamic in time and space. Effective technical solutions for improved detection of plant diseases are highly desirable. Various research groups performed scientific studies in the field of assessing plant diseases in different host-pathogen systems (Al Masri et al. 2017;

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Sugiura et al. 2016; Wahabzada et al. 2016; Hillnhütter et al. 2011). Important insights on the basic principles of interactions of plant pathogens and pests with plants and their influence on the optical properties have been generated (Simko et al. 2017; Mahlein 2016; Bock et al. 2010; Sankaran et al. 2010; West et al. 2003). For the improvement of precision agriculture and plant phenotyping, highly sensitive sensors are developed and need to be investigated to enable automated disease detection and improve standardized rating methods (Simko et al. 2017; Mahlein 2016; Fiorani and Schurr 2013).

### **The demand for precision agriculture – real-time detection of plant diseases in the field**

Optical sensors are non-invasive measurement systems that can be used on the same individuals over time. Different sensors such as RGB, 3D, fluorescence, thermography, and hyperspectral imaging (HSI) enable the characterization of relevant plant parameters (Mahlein 2016). Recently published smartphone applications established an automated identification of sugar beet diseases (Hallau et al. 2017). Here, a conventionally integrated smartphone camera has been used with a convenient software surface. Such smartphone applications are mainly beneficial for private use, agricultural service, and farmers because the disease symptoms must be already visible. The throughput is limited and it has to be linked to a threshold-based, integrated plant protection measure. These studies demonstrated, that collections of imaging data from diseased leaves can be used to develop sophisticated machine-learning approaches for early disease detection by RGB sensors. Accurate disease detection is also possible with thermographic imaging because the plant temperature correlates with its water balance and transpiration, which are affected by plant diseases (Al Masri et al. 2017; Simko et al. 2017). This method is highly sensitive, but limited in the ability to identify specific diseases and differentiate them from abiotic factors that can induce water stress, respectively. Similar accuracy in stress detection with a low stress specificity is also observed for chlorophyll fluorescence imaging (Simko et al. 2017; Mahlein 2016).

Hyperspectral sensing enables the detection and differentiation of abiotic and biotic stresses, which opens new opportunities for field phenotyping and management (Ge et al. 2016). Across application areas on

different scales, hyperspectral remote sensing approaches are feasible to detect diseased plant spots in the field (Hillnhütter et al. 2011; West et al. 2003). This permits precise and short-term applications in the field and the mapping of landscapes with relevant crop and cultivation parameters for future precision field management (Mulla 2012). But the characterization of a specific disease is still challenging with hyperspectral remote sensing. The spatial resolution of these sensors is often not high enough for identifying plant diseases below a management threshold. Within this context, hyperspectral close range or proximal imaging is more promising and able to characterize plant diseases in space and time (Mahlein et al. 2012).

Based on recent experience, demands for specific sensors still have to be specified in future. The application environment and the plant-pathogen system are the defining factors within this context. Different studies and their communication into society, to companies, and farmers aspire high hopes for future innovations. For an exhaustive evaluation and critical discussion of prospects and actual merits, recent achievements and limitations have to be outlined. Application of optical sensors in the field is often confronted with abiotic factors, which impede disease detection (Moshou et al. 2015). Beside natural illumination, the spectral influence of rain and the remaining water on the plant needs to be evaluated. Wind causes plant movement during measurements, which degrade the record quality and by this the data accuracy. Snap-shot cameras will reduce this phenomenon, because currently hyperspectral cameras are mainly whisk broom scanners, push broom and full-frame cameras (Thomas et al. 2017). However, until now these snap-shot cameras were not available with an adequate spatial and spectral resolution. In addition, the assessment of important wavelengths for specific demands can be used to develop multispectral camera systems such as digital cameras with specific LED configurations (Grieve et al. 2015). This will reduce measurement time and data size, and can realize real-time applications. However, multiple biotic stresses have to be considered such as mixed infection by fungal plant pathogens, pests, and feeding damage by animals. For field applications, a controlled measurement system needs to be developed. The sensor carrier and vehicle must be synchronized and adapted to the information to be collected. As an example, drone applications have high accuracy, scale independence, and rapid movement (Sankaran et al. 2015). Though, limitations and

challenges of drones are still the time of flight, wind sensitivity, lift capability and ventilation, which can move the crop during close range imaging at low-altitude. In addition to existing sensor tractors and manual sensor vehicles, an autonomous robot could improve data collection with optical sensors in precision agriculture (Mueller-Sim et al. 2017; Andrade-Sanchez et al. 2014). These and further supporting systems for sensors in agriculture are still under development and evaluation. Testing of HSI in field show different specific demands, which depend on the crop and measurement situation or on the specific parameter of interest (Mahlein 2016).

### Development of reliable data analysis

HSI is able to provide relevant information about different plant parameters. In fact, HSI records the electromagnetic spectrum that is reflected from plants. The optical information summarizes the plant compartments, type of leaf, the surface texture, the leaf age, etc. To extract relevant information on the plant status, the reflectance signature needs to be analysed and characterised; this can be done manually. The combination and calculation of narrow or broad wavelengths ratios were developed to establish relationships of hyperspectral reflectance signatures to plants and their biophysical variables in remote sensing (Thenkabail et al. 2000). These are described as spectral vegetation indices and result in a reduction of data dimension. The Normalized Difference Vegetation Index (NDVI) is a common spectral index to assess plant vitality by the green biomass and chlorophyll content from remote sensing (Gamon and Surfus 1999). During the last decades, many sophisticated spectral vegetation indices were developed and adapted for proximal plant sensing approaches e.g. for plant disease detection (Mahlein et al. 2013; Delalieux et al. 2007; Steddom et al. 2005). The development of spectral vegetation indices depends on the connection of the spectral reflectance with biochemical and biophysical properties, which requires intensive investigation and validation.

Therefore the extraction of the reflectance signatures pixel by pixel is required. Such analysis is labour intensive because hyperspectral images can consist of millions of pixels. The selection of regions of interest pixels is non-objective and limited if no visible changes on the spatial hyperspectral images occurred. In addition, HSI

data sets of time series experiments can contain several gigabytes or even terabytes (Kersting et al. 2016). However, for the interpretation of the spectrum, signatures must be extracted from pixels of interest of the hyperspectral image. Changes or differences in the extracted spectral signatures during plant-pathogen interactions, can be assessed by calculations of the spectral differences, ratios or derivations (Kuska et al. 2017; Mahlein et al. 2012). Data driven and machine learning approaches can reduce the labour intensity and could enable the detection of attributes on hyperspectral images such as pre-detection and allocation of plant diseases (Behmann et al. 2015). Among machine learning approaches, unsupervised and supervised methods for classification and clustering can be applied. Unsupervised machine learning tries to find key pattern in the data without additional manual input. In contrast, supervised machine learning requires a set of labelled training data, which consists of described examples e.g. image annotations and pixel allocations. Common classification and clustering methods for crop hyperspectral image analysis are: k-means (unsupervised), IsoData (unsupervised), self-organizing maps, support vector machines, spectral angle mapper and artificial neural networks (Kersting et al. 2016; Mahlein 2016; Moshou et al. 2015; Behmann et al., 2015). However, pre-labelled plant data are difficult to obtain for early plant-pathogen interactions. Recent studies by Wahabzada et al. (2016) established a machine learning method to wordify hyperspectral reflectance signatures during three different barley pathogenesis (powdery mildew, brown rust, and net blotch). This could enable a modern art of spectral libraries, which contains spectral features of plant diseases and the plant health status. The collection of characteristic hyperspectral signatures of plants would be a global benefit, also opening doors for non-experts. In addition, such data collection could be integrated to common field-management and online-tools e.g. performance maps, weather data and forecast models. This would enable a reliable tool for early and precise plant protection measures.

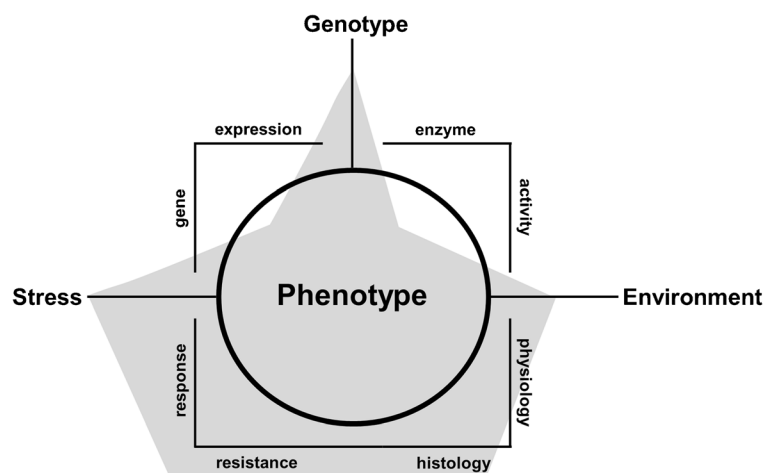
### Phenotyping: a key element to establish optical sensors in applied practice

Sensors can be used within the phenotyping process after several hybridizations and generation of a set of genotypes of interest that must be investigated in different

environments and under different conditions. Qualitative characterization of the genome expression to plant function in a given environment is done by the visual estimation of human raters. This step is defined as the phenotyping process (Fiorani and Schurr 2013). Phenotyping is the visual description and assessment of plants from single organs to the canopy during all growth stages (Fiorani and Schurr 2013). This includes the plant growth rate, architecture, leaf color, health status, and detection of abiotic and biotic stress symptoms and their severity. Depending on the testing property, phenotyping process may be necessary during the vegetative and generative phases of a plant. However, it requires a large human effort and the testing of certain environments limits the throughput; this is described as the phenotyping bottleneck (Furbank and Tester 2011). In addition, traditional visual estimation of plant disease severity is prone to errors because plant-pathogen interactions sites are on the cellular and leaf level and the assessment is subjectively influenced by the rater (Bock et al. 2010; Nutter et al. 2006). To overcome these circumstances, objective methods are required but early plant-pathogen interactions are in the submillimeter size, which limits the early detection even by applying HSI (Mahlein et al. 2012). An increased spatial resolution of hyperspectral cameras can be obtained by hyperspectral microscope setups (Kuska et al. 2015). With this approach, small and subtle pathogenesis and resistance related reactions of plants against pathogens can be investigated (Kuska et al. 2017).

Optical sensors enable new possibilities for basic research studies and can be implemented in breeding routines and field management. Pinto et al. (2016) investigated the sun induced chlorophyll fluorescence using HSI and established a method to quantify spatio-temporal dynamics of the fluorescence of crop canopies and photosynthetic activities. This enables the assessment of the photosynthesis performance of vegetation canopies. Nevertheless, spectral images must be also linked to biologic processes, especially during plant-pathogen interactions. Recent studies revealed the feasible analysis of plant leaf chemicals and metabolites using HSI (Pandey et al. 2017; Arens et al. 2016), which increases the potential applications of HSI for plant resistance breeding and precision agriculture.

As a short summary of the state of the art, it has been demonstrated that HSI performs for detection and assessment of specific plant diseases, plant resistance responses, and for determination of abiotic stresses (Fig. 1). In addition, plant physiological and histological changes can be assessed by HSI and support the biological interpretation of a plant hyperspectral image. Further investigations to link molecular data with HSI data are still necessary. This will open new possibilities in basic research for the development of innovative plant protection strategies and for plant resistance breeding (Fig. 1). These findings could be used to improve and calibrate resistance- and disease-screening systems by applying HSI.



**Fig. 1** Parameters influencing the plant phenotype. Furthermore, plant parameters and phenotype relevant factors which can be detected and assessed using hyperspectral imaging are indicated by the shape of the hexagon. Different stresses can be determined and assessed by hyperspectral imaging. Physiological and

histological studies are mainly used for the biological interpretation of the reflectance spectrum like for plant pathogen resistance detection. The influence of specific gene expression profiles and enzyme activities on the spectral reflectance pattern of plants are still unknown

Furthermore, for plant resistance phenotyping the results from proximal sensing need to be transferred on the plant and field scale. State-of-the-art phenotyping greenhouse facilities were the first step to establish high throughput screening systems (Yang et al. 2013). In such approaches, whole plants are measured and new important parameters from spectral imaging can be considered with information, on plant architecture, leaf angle, and leaf overlapping (Thomas et al. 2017; Virlet et al. 2017). A future improvement may be the fusion of different sensor approaches such as 3D cameras for spatial normalization of spectral images (Behmann et al. 2016). This fusion has to be performed on the data scale.

Methods based on optical sensors can overcome current limitations of disease detection and rating, and can generate objective data and standardized parameters. A positive consequence will be a more precise plant protection measure and higher objectivity in plant phenotyping processes. Both come with a reduced human effort. However, existing techniques have to be critically evaluated and calibrated to each specific disease and situation individually. Hyperspectral handheld cameras can enable more flexible applications without carrier platforms (Behmann et al. 2018). Therefore, the development of faster measurement options, auto focus and automated integration time settings in hyperspectral cameras are desirable to make HSI an effective practical tool in agriculture and plant phenotyping. In addition, user-optimized data analysis pipelines and measurement methods must be developed to establish standardized conditions. There will not be one all-inclusive solution in the near future. Overall, it is believed that optical sensors will play a key role in the coming smart farming activities to ensure sustainable agriculture due to improvement in plant breeding and field monitoring in precision agriculture and integration in practical tools. This movement will be only successful if experts with different backgrounds across science, industry, extension service, and farmers work together and establish a common vision of reliable approaches.

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**Competing interests** The authors declare that they have no competing interests.

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