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PERSPECTIVES

From Detection to Protection: The Role of Optical Sensors, Robots, and Artificial Intelligence in Modern Plant Disease Management

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Abstract

In the past decade, there has been a recognized need for innovative methods to monitor and manage plant diseases, aiming to meet the precision demands of modern agriculture. Over the last 15 years, significant advances in the detection, monitoring, and management of plant diseases have been made, largely propelled by cutting-edge technologies. Recent advances in precision agriculture have been driven by sophisticated tools such as optical sensors, artificial intelligence, microsensor networks, and autonomous driving vehicles. These technologies have enabled the development of novel cropping systems, allowing for targeted management of crops, contrasting with the traditional, homogeneous treatment of large crop areas. The research in this field is usually a highly collaborative and interdisciplinary endeavor. It brings together experts from diverse fields such as plant pathology, computer science, statistics, engineering, and agronomy to forge comprehensive solutions. Despite the progress, translating the advancements in the precision of decision-making or automation into agricultural practice remains a challenge. The knowledge transfer to agricultural practice and extension has been particularly challenging. Enhancing the accuracy and timeliness of disease detection continues to be a priority, with data-driven artificial intelligence systems poised to play a pivotal role. This perspective article addresses critical questions and challenges faced in the implementation of digital technologies for plant disease management. It underscores the urgency of integrating innovative technological advances with traditional integrated pest management. It highlights unresolved issues regarding the establishment of control thresholds for site-specific treatments and the necessary alignment of digital technology use with regulatory frameworks. Importantly, the paper calls for intensified research efforts, widespread knowledge dissemination, and education to optimize the application of digital tools for plant disease management, recognizing the intersection of technology's potential with its current practical limitations.

Keywords: accuracy, artificial intelligence, optical sensors, plant disease detection, robotics

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Driving Motivation

Agricultural crop production, including the production of food, feed, and fiber, faces multiple challenges. Crop science and agricultural practice are caught between sustainable productivity increases, challenging and changing environmental conditions, increased biotic and abiotic stresses, and shifting policy frameworks. Digital agriculture is a burgeoning approach that can meet the challenge of creating a sustainable global agricultural production system (Basso and Antle 2020). Plant diseases reduce the quality and quantity of crop yield, and integrated crop protection strategies need to be implemented while addressing environmental concerns and being sensitive to regulatory practices. Regulations continue to tighten conventional plant protection products to mitigate environmental risks and protect nontarget organisms and human health. A recent strategic position paper, the European Green Deal with the Farm to Fork (F2F) Strategy, describes aims to reduce the number of conventional pesticides applied to crops by 50% by 2030 and to promote organic production (Purnhagen et al. 2021). The challenges demand a new paradigm for agricultural production and implementing innovative approaches in crop protection. Integrated pest and disease management (IPM) aims to utilize the breadth of agronomic measures for disease control, including cultivation of resistant varieties, crop rotation and biotechnology, and biological or conventional chemical-based plant protection. Decision-making is based on accurate diagnosis and disease quantification. Currently, management decisions for disease control rely on a combination of visual detection and monitoring by experts, incorporating digital expertise and prediction systems based on weather data and epidemiological parameters of plant diseases (Madden and Hughes 1995; Ristaino et al. 2021; Rossi et al. 2010).

Plant disease prediction models have been developed as either data-driven (empirical) or concept-driven (mechanistic) models that use mainly within-season weather as the key variable, together with other agronomic and biological factors. Existing literature has recently thoroughly investigated and reviewed the principles of decision support or early warning systems (Bregaglio et al. 2022; Dong et al. 2020). To develop and validate such models, experimental data from several years and differing environments are required, preferably at a high resolution (Ojiambo et al. 2017). Advisory services and farmers can use decision support systems that integrate the prediction models to optimize crop protection and maximize yield (Hughes 2017). Rossi et al. (2019) stress that the use of decision support systems has been restricted to certain geographic areas and crops and a limited group of users, mainly in developed countries. There is an opportunity to promote the expansion of decision support system use once the hurdles in data collection, processing, and dissemination are overcome (Deichmann et al. 2016). Integration and calibration of “conventional” plant disease prediction models with high-resolution sensor data offers the opportunity to validate the outcome of these models and vice versa (Camino et al. 2021; Zhang et al. 2014). It is now acknowledged that not only are digital technologies of technical and economic value in developing novel disease management approaches, but their use will also impact the environment and thus affect social and ethical aspects of crop production (Klerkx et al. 2019; Lajoie-O’Malley et al. 2020; Wegener et al. 2019).

Interestingly, there are parallels between the introduction of IPM in the mid-1960s (Carlson and Castle 1972; Smith and Reynolds 1966; Smith and van den Bosch 1967) as a revolutionary concept providing a sustainable approach to plant protection and the recent integration of digital technologies into the IPM toolbox. IPM has endeavored to promote sustainable forms of agriculture, pursued sharp reductions in synthetic pesticide use, and thereby resolved a myriad of socioeconomic, environmental, and human health challenges (Deguine et al. 2021). High demands and expectations were placed on this concept but were not fully met in agricultural practice, as reviewed by Deguine et al. (2021). Inconsistent definitions and inconsequential implementation by farmers are considered potential reasons for the poor uptake. However, IPM is a dynamic concept, closely linked to plant protection via conventional pesticides, which adapts fast to new, emerging situations and challenges—and by this measure is a success story, even if the value is difficult to measure. Hundreds of definitions of IPM exist worldwide, depending on the disciplinary background, the experience, and the location in the world. Thus, we see multiple similarities and parallels with digital technologies for crop protection. It is a nascent, emerging toolbox with great potential to contribute to today’s challenges and demands. There are thousands of views and focal points, and a meaningful knowledge transfer is crucial to establish a common understanding for scientists and stakeholders, which is a necessary basis to achieve its full potential.

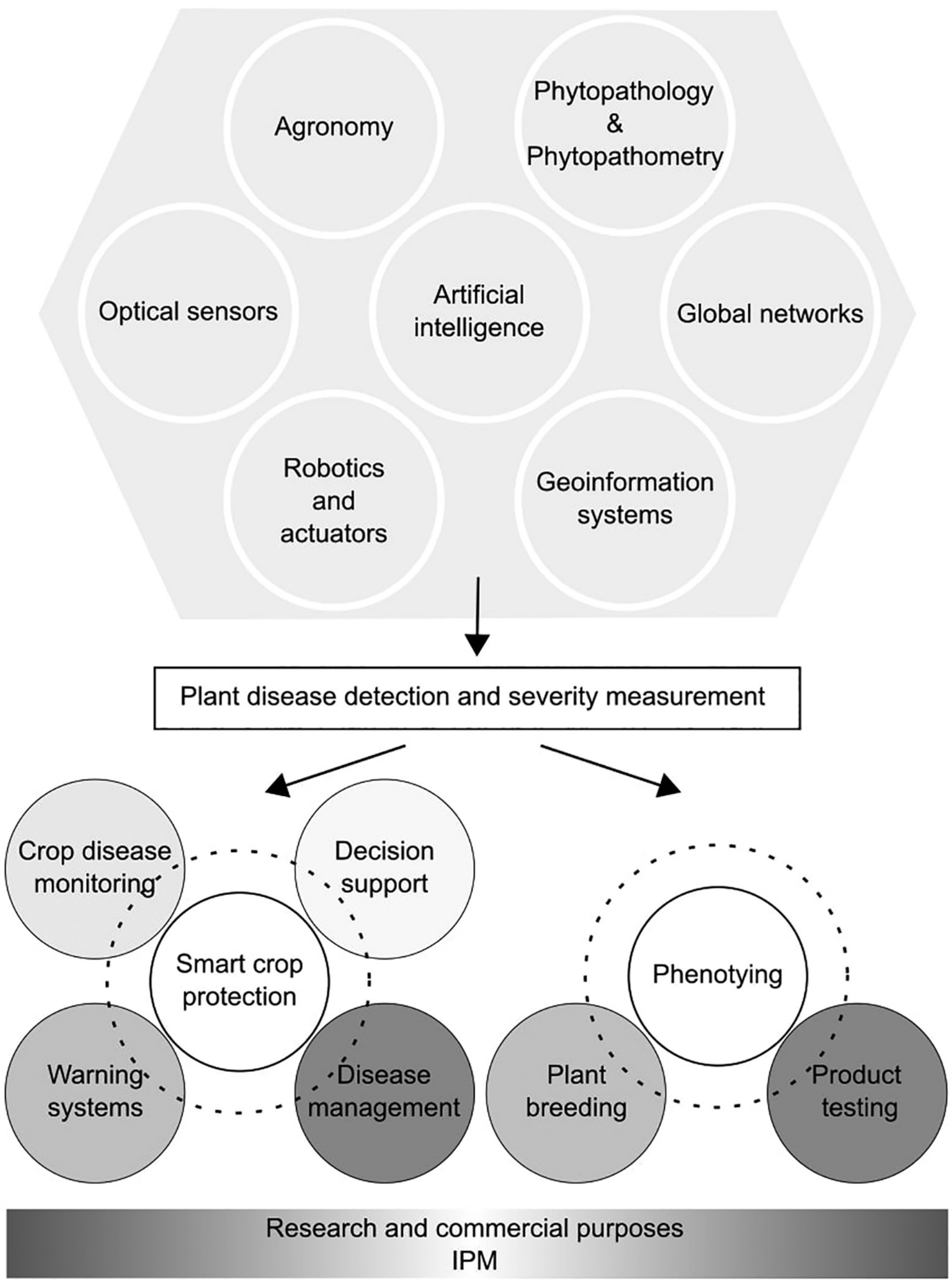
During the last 20 years, technological innovations have developed rapidly and provided an opportunity to revolutionize plant protection, particularly detection, monitoring, and decision-making. The well-established routine of decision-making can be expanded by integrating digital technologies and elements of phytopathometry (disease measurement). Digital technologies in agriculture can be classified into six groups: (i) optical sensor systems, (ii) robotics and actuators, (iii) geoinformation systems, (iv) mechanistic forecasting and early warning models, (v) artificial intelligence (AI) and computing power, and (vi) global networks (Bogue 2016; Mahlein et al. 2018). Based on innovations in these six areas, smart agriculture and smart plant protection are under development and have been prioritized by several corporations in the agricultural sector. The motivation to embrace digital technologies for disease management is driven first by the need for improved accuracy in disease monitoring given that visual estimates of disease severity are prone to errors (Bock et al. 2010; Nutter et al. 2006). Second, digital technologies offer an opportunity for automation and cost-saving routines, especially on a large scale. Imaging sensors enable the characterization of selected plant variables. Frequently used technologies are red-green-blue cameras with high resolution (Görlich et al. 2021), multispectral or hyperspectral imaging (Thomas et al. 2018), 3D technologies (Paulus 2019), thermography, and chlorophyll fluorescence imaging (Mahlein 2016). Detailed information on the measuring principles of the individual sensor types can be found in existing review articles (Bock et al. 2020, 2022; Mahlein 2016; Mahlein et al. 2019; Paulus 2019). In combination with powerful analytical routines from AI (e.g., supervised or unsupervised classification, regression models, neural networks), useful information can be extracted from unstructured and complex datasets and used to provide interpretable results (Behmann et al. 2015). AI has attracted much public attention. However, no clear and common definition of AI exists in the community (Wang 2019). The most appropriate and accepted definition is likely “information or computer systems able to perform tasks normally requiring human intelligence.” Within this context, multiple studies have applied and developed AI in the form of machine learning or computer vision approaches to detect, predict, or identify plant diseases. Recently, expert knowledge has been integrated with machine learning approaches, which enhances rational machine learning routines (Schramowski et al. 2020). For plant disease management, the use of digital technologies can be applied directly in the producers’ field in a decision-support role. Further, they can be applied in plant breeding, pesticide development, and other research contexts where disease must be detected or quantified. In plant breeding, digital technologies have supported the automation of screening and breeding routines for the identification and development of disease-resistant or -tolerant varieties or compound testing, respectively. The associated disciplines and concepts are presented in Figure 1.

With the advances in digital technologies, the science of disease detection and measurement enters a new era with many new terms and concepts, as phytopathometry is no longer the sole realm of expert visual assessment by an individual. A recent glossary (Bock et al. 2022) provides an updated list of terms used in phytopathometry (including those used in digital technologies).

New Achievements—Continuing Restrictions

Several review articles have highlighted the benefits of sensors, sophisticated data analyses, and automation of disease detection and monitoring methods developed by multidisciplinary teams (Bock et al. 2022; Fahlgren et al. 2015; Mahlein 2016; Ruwona and Scherm 2022; Sankaran et al. 2010). The articles are complemented by research studies, developing and establishing advanced digital sensor-based approaches for accurate estimation of disease incidence, severity, and the effects of diseases on yield and product quality (Bohnenkamp et al. 2021; Chaerle et al. 2009; Görlich et al. 2021; Mahlein et al. 2013; Pethybridge and Nelson 2018; Schramowski et al. 2020). A list of sensor-based studies is provided by Bock et al. (2020; see Tables 4 and 7). The research has generally used a noninvasive sensor system in combination with sophisticated approaches for data analysis based on machine learning. Monitoring crop plants for health status (diseased versus non-diseased) is addressed as a binary task. The studies cover a range of host-pathogen systems, the type and capability of sensor equipment, and disease variables measured and vary in the machine learning methodology and data analysis pipeline. However, during pathogenesis, there is a characteristic progression from healthy to diseased, showing unspecific symptoms. In this phase in particular, the detection accuracy might be low, and confusion with other stress-causing factors may occur. Some studies are performed under controlled conditions in a laboratory setting using digital technology to assess disease at a leaf or single plant scale (Bohnenkamp et al. 2021; Gold et al. 2020; Kuska et al. 2015). In a greenhouse environment, both control algorithms for decision-making and early warning in disease prevention (Katsoulas et al. 2021) and sensor applications for direct detection have been developed (Liu et al. 2023; Schor et al. 2017). Other studies have addressed disease detection and quantification under challenging conditions in the field (Heim et al. 2018; Kalischuk et al. 2019; Selvaraj et al. 2020). Indeed, the integration of sensors on a robotic platform is a relatively recent development: Unmanned aerial vehicles (UAVs) and unmanned ground vehicles provide the potential to fully automate disease detection and quantification at different scales, providing a high-throughput system (Ampatzidis et al. 2017; Barbedo 2019). UAV in-field disease detection follows a series of procedures: (i) flight mission and image capture, (ii) image processing and development of ortho mosaic images, (iii) plot extraction, (iv) single plant identification based on computer vision, (v) leaf detection using deep learning, and (vi) symptom classification by machine learning (Fig. 2) (Barreto et al. 2023a; Ispizua Yamati et al. 2024). Most of the studies to date have tracked and studied only one disease compared with healthy plants, and only very few studies have investigated and compared different diseases (Bohnenkamp et al. 2021; Mahlein et al. 2013) or used multiple stressors (Chaerle et al. 2009). Some studies have enabled reliable and accurate early detection of plant diseases before visible symptoms appeared (Rumpf et al. 2010; Zarco-Tejada et al. 2018).

FIGURE 1
The use of digital technologies to detect and measure plant disease provides a basis for smart crop protection in commercial agriculture and the application of the technology in associated research.



Integrating Digital Technologies into IPM

The basis for accurate and sensitive disease detection and measurement relies on a well-designed combination of digital technologies (Mahlein et al. 2018). As Bock et al. (2022) emphasized, accuracy is the closeness of an estimate to the assumed "gold standard" or true value. Sensitivity as a statistical measure can be understood as a proportion of positives that are identified correctly. Under controlled conditions, complex sensor systems, such as hyperspectral imaging, which has hundreds of wavebands in 3D-hyperspectral data cubes, or chlorophyll-fluorescence with specific demands on the measuring routine, such as dark adaptation, are adequate for the task. In these conditions, measuring setups can be designed based on the demands of the sensing system (in general by a static measuring chamber with optimal illumination conditions, a stable distance between the sensor and the object, and stable temperature conditions). In contrast, measuring setups in the field must be designed based on the demands of the cultivation system and environment (all aforementioned aspects can be variable). Furthermore, under controlled conditions, time series measurements can be performed easily and compared. Detailed information on the host-pathogen interaction, disease dynamics, and epidemiology should be available and could be retrieved using data-intensive approaches based on digital technologies. In the field, detection and quantification are more challenging, and the sensor system must be robust, lightweight, and easy to use. A discerning equilibrium among throughput, data quality (noise and stability), and spectral and spatial resolution must be achieved. Less complex multispectral or high-resolution red-green-blue cameras are therefore preferable.

There remain challenges to developing and transferring existing digital technologies to function accurately in the field, greenhouse, orchard, or other cultivation systems. Existing models and approaches often cannot be generalized among different environments, and sensor settings may need adjustment even among varieties within one crop species. As shown in various research articles, the extrapolation of results from controlled conditions to the field remains challenging (Appeltans et al. 2022; Bohnenkamp et al. 2021).

However, it is crucial to derive parameters or characteristics from sensor data for decision-making. Only a few studies have addressed the assessment of well-characterized parameters such as disease incidence or disease severity in the field (Barreto et al. 2023a). Assessing disease incidence and disease severity digitally has the potential to create site-specific application maps and reduce the amounts of pesticides applied (Barreto et al. 2023b; Günder et al. 2022; Lizarazo et al. 2023). This information can guide robots equipped with spot-spraying capability or direct spray drones to target plant protection measures specifically where they are needed. More research and development of digital technologies are needed for crop disease detection, quantification, monitoring, and subsequent control. Another area of research where the practical use of digital technologies has huge applications is in plant breeding for disease resistance. With relatively controlled and managed field conditions, the implementation of sensor-based disease ratings and monitoring has been demonstrated (Görlich et al. 2021).

Digital technologies can be integrated with IPM by substituting some current methods and supporting various components. The potential of digital technologies for IPM goes further. The entire

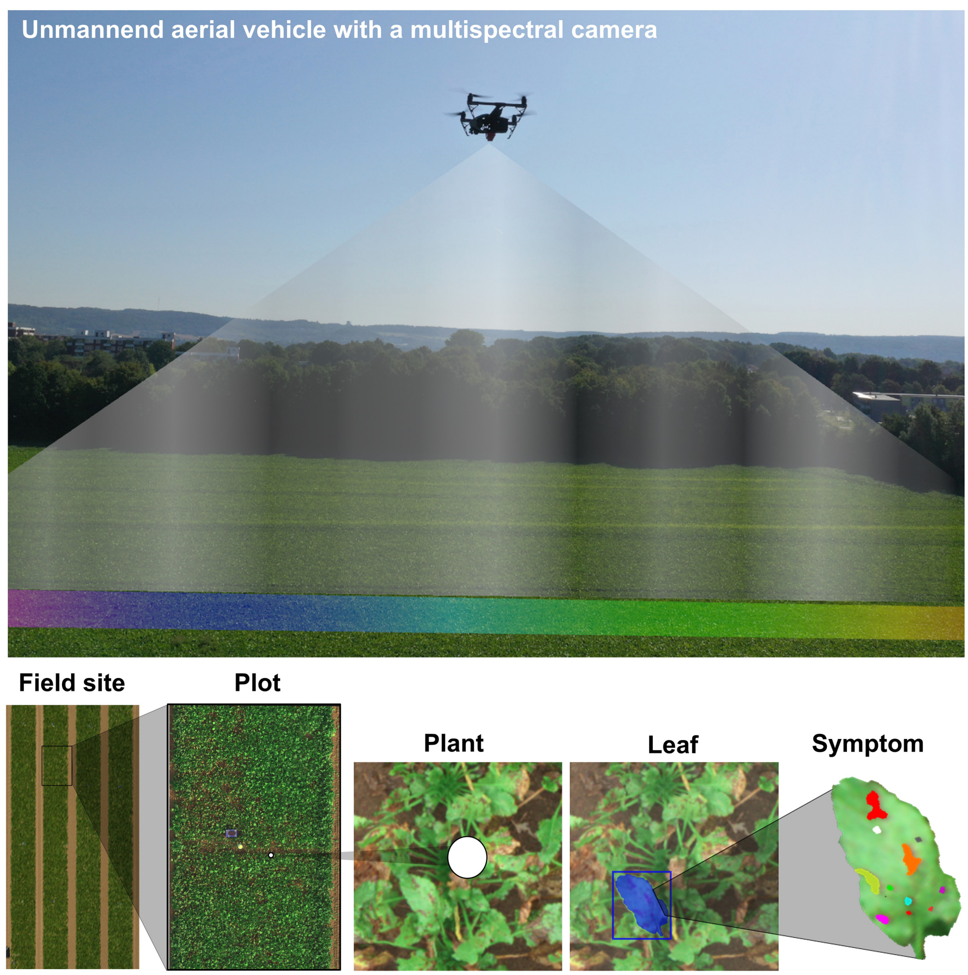


FIGURE 2
Assessment of disease symptoms on the scale of disease incidence (DI) and disease severity (DS) using an unmanned aerial vehicle (Quadro-copter, DJI Inspire 2, Da-Jiang Innovations Science and Technology Co., Ltd., China) equipped with a multispectral camera (RedEdge-M, MicaSense, U.S.A.). The camera provides three visible spectral bands (475 nm [blue], 560 nm [green], 668 nm [red]) and two near-infrared (NIR) spectral bands (717 nm [red edge], 840 nm [NIR]). Images show a sugar beet variety trial near Göttingen, Germany. Sugar beet plants were diseased with Cercospora leaf spot. The analysis pipeline includes (i) flight mission and image capture, (ii) image processing and development of ortho mosaic images, (iii) plot extraction, (iv) single plant identification based on computer vision, (v) leaf detection using deep learning, and (vi) symptom classification and assessment (e.g., DI or DS) by machine learning.

decision-making process, including initiating plant protection measures, can benefit from sensors, robotics, and AI. Sensor data can be utilized to generate application maps, reflecting the variable disease occurrence in space. Performing site-specific disease control is feasible while also reducing the input of pesticides (Mahlein et al. 2018; West et al. 2003; Yang et al. 2016). Agricultural production systems can be redesigned in a completely new way. Diversifying agricultural fields and reducing field size at the landscape scale can result in beneficial effects on biodiversity. This is now a practical proposition by utilizing small, automated equipment, guided by optical sensors. Concepts currently under development are spot farming (Wegener et al. 2019) or diversifying fields in patches, considering site-specific characteristics and risk of disease occurrence while promoting ecosystem services (Bellingrath-Kimura et al. 2021). Furthermore, digital documentation of plant protection measures is feasible and will support farmers in ensuring good agricultural practices. Software-embracing approaches and routines to consider and omit protected areas, such as field margins or bodies of water, when applying plant protection compounds have been developed and are available to farmers. These are important complementary components to improve and support the sustainability of crop protection and crop production. Furthermore, it should be noted that sensor technologies used for disease detection and quantification enhance our understanding of diseases and symptom characteristics and advance the science of phytopathometry.

Additionally, we must transfer recent developments and trends in digital technology to farmers and advisory services to ensure that the benefits of the technologies for plant disease management are fully realized. In terms of digital technologies for plant protection, bidirectional knowledge transfer will improve the applicability and acceptance of innovation. The benefits will include but are not limited to early detection and accurate quantification, improved decision support, more targeted crop management practice, and less impact on the environment and human health. The platforms for digital technologies are already diverse and will doubtless continue to morph. Mobile phones, tablets, and other computers enable a fast and seamless transfer of data and associated recommendations or other information; any existing usage or communication barriers can be overcome by continuing to implement and adapt novel technology (Hallau et al. 2018; Pethybridge and Nelson 2018). The potential in developing regions of the world is particularly profound, where farmer information systems using mobile applications can be a fast-track approach to improve and impact management practices (da Silveira et al. 2023; Duncombe 2014). In terms of digital technologies for plant protection, bidirectional knowledge transfer will improve the applicability and acceptance of innovation.

Aspects that cannot be addressed in detail in this article but need further consideration are data security, data rights, ethical considerations, and risk factors of digitalization in IPM. As Tzachor et al. (2022) emphasized, systemic risk factors of AI in agriculture need to be considered, such as interoperability, reliability, and relevance of the data. We strongly believe that an open data policy will be a driver of innovation. FAIR data principles (findability, accessibility, interoperability, and reusability) must be adapted and considered for agricultural applications (Top et al. 2022). Corporations or governments that seek to protect information will impede the innovation needed for developing these applications. A concept of equality and transparency will contribute substantially to the success of IPM digitalization.

Open Questions and Unsolved Issues Regarding Digital Technologies and How Best to Address Them

The following list considers relevant fields of action, pointing out the individual research needs and resulting impact. The list cannot claim to be comprehensive, and each point must be considered individually.

- **How early should plant diseases be detected?** Detection before symptom development has been demonstrated in laboratory settings, but how can the technology be transferred effectively to the field, where so many variables can impact sensor-based detection? This central question could be the topic of an entire article. Presymptomatic detection is highly dependent on the individual pathosystem, its biology, and epidemiology. Not every disease must be detected before symptoms are visible. To cite one example with a very long latent phase, citrus greening disease (huanglongbing) can lead to the loss of entire orchards if not detected before symptoms appear because infected trees should be removed as an inoculum source (Bassanezi et al. 2020). Other diseases produce infectious structures as soon as the first symptoms appear after the initial infection and produce multiple generations during the growing season. Red-green-blue and multispectral sensors cannot provide sufficient information for early detection, but hyperspectral images and alternative approaches (e.g., photonics) in combination with classical diagnostics have shown promise. With regard to decision-making in IPM, threshold values indicate the disease incidence or severity at which control with plant protection products is economically reasonable (Steinmann et al. 2021). Thus, a system must be sensitive enough to assess thresholds correlated with disease incidence or disease severity, and each digital strategy must be matched to the individual host-pathogen system (Barreto et al. 2023a). Furthermore, combining optical sensor data, epidemiological data, and environmental data can improve precision and reliability within the context of the disease triangle because a higher information content can be beneficial (Mahaffee et al. 2023). There are a few data fusion and information fusion techniques (in terms of integrating data from different kinds of sensors into a model) that can help with this task (Barbedo 2022b).
- **How accurate should sensors and other technologies be, and how do we reference them?** Accuracy, particularly with imaging sensors, requires a robust gold standard and very large datasets. AI models, and especially those based on the concept of deep learning, have reached a level of maturity sufficient to tackle virtually any classification problem. The bottleneck is in the data. If the classification/measurement is to be performed in the field under uncontrolled conditions, all possible sources of variation need to be considered. As a result, datasets usually need to be large and representative of the variability associated with the problem. To make matters more complicated, the image annotation process by a human is subjective and slow. In many cases, the amount of information contained in the data (images or other kinds of data) is not enough for unambiguous answers. In such cases, data fusion (an approach that is quickly gaining momentum) or augmented data may be the only option for a reliable automated system (Barbedo 2022a). There is also a need for accurate disease severity measurement. For the information to be useful, we must know not only what is there but also how much. To obtain this information, sensor-based methods of assessment are available but could often be unreliable concerning accuracy. To determine the level of accuracy in particular cases, quantitative ordinal scales (Chiang et al. 2014) have been used as gold standards against sensor-based methods, but this relies on estimates made by human raters who assign values to visually observed samples on scales that are constructed based on grouping of discrete units into categories; often, these scales use very few categories. In such cases, a rater's measurement has been regarded as the reference value. When a quantitative ordinal scale is being used for reference or validation, it is crucial to identify its structure (i.e., does the scale have equal or unequal

intervals? What is [are] the interval width[s]?). However, there are very few investigations into sensor-based measurement that have considered the ramifications of using a quantitative ordinal scale for validation. Therefore, further development of quantitative ordinal scales for validation of sensor-based measurement needs to be considered.

- **The quality of data obtained by optical sensors is critical. Is the quality of the data we currently collect with optical sensors high enough to enable accurate, reliable detection, considering the spatial and temporal diversity present in a given environment?** Data availability and data quality are crucial for research, as well as for practical application in the field, greenhouse, and other growing systems. Three aspects related to data quality need to be considered: (i) Do the data cover the entire variability associated with the problem, (ii) the quality of the annotation ([i] and [ii] are discussed under the previous point), and (iii) the quality of the data itself (Behmann et al. 2015; Dong et al. 2022)? In the case of optical sensor data, unfavorable illumination, blur, inadequate angles, and more can reduce data quality. However, deep learning models show remarkable robustness to low-quality images if these are not too numerous (Li and Chao 2021). In general, this is a problem mostly associated with the time of image capture, environmental factors, manual versus automatic image capture, and employing multiple individuals to capture the images for model training. Statistical methods exist to detect and quantify errors within data and to assess the data quality, such as principal component analysis or artificial neural networks. Through a systematic review, Teh et al. (2020) found that methods proposed to address physical sensor data errors cannot be directly compared and needed to be tailored to each individual setting and data source.
- **How can we address the complexity of dynamic and diverse crop architectures and geometries in different field crop species stands during the growing season?** For example, how can we assess disease symptoms occurring on lower leaf levels in closed canopies? Are there ways disease in the lower canopy can be modeled reliably based on disease measured or detected elsewhere? Are additional light sources needed, and how can we best use these in the canopy where leaves will still be obscuring each other? What about use of digital technologies in tree crops and their canopies? To some extent, hyperspectral imaging can detect the effects of diseases from a top-down view, but for a direct assessment of symptoms on leaves obscured under other leaf layers, new imaging settings with, for example, miniaturized autonomous vehicles (rovers, UAVs) may be needed. However, much further research and development are required before swarms of robots can be utilized to monitor crops for disease (Albiero et al. 2022; Schranz et al. 2020). Recently, functional and structural plant models for different crops and cropping systems have become available (Bailey 2019). These models can be the basis for digital twins of crops, recreating the behavior of crops in diverse environments and under different abiotic and biotic stresses (Purcell et al. 2023; Skobelev et al. 2020).
- **How can we mitigate the impact of environmental factors on the accuracy and reliability of optical measurements under field conditions?** Environmental factors (sunlight, shadow, wind, rain) impact the data quality and information content. In some cases, calibration and normalization are possible (varying illumination conditions); in other cases, the use of sensor systems will not be possible (wind or rain) (Thomas et al. 2018). Transfer of models developed in the laboratory or plots will need to be ramped up and adapted to be of practical use at the full range of spatial scales, particularly the field scale but possibly even larger scales. So far, a direct transfer from the lab to the field failed in several research studies (Bohnenkamp et al. 2019, 2021), and the reasons still need to be investigated. It is likely that the aspect of external factors will be addressed by larger datasets for training algorithms and innovative machine learning algorithms that are better able to cope with varying illumination conditions, for example. In terms of sensor development, robust snapshot systems with relatively low integration times could further counteract quality losses. A new trend from machine learning that may contribute to solving this problem are general purpose foundation models (Chen et al. 2024). The first promising applications have been demonstrated in healthcare. Despite their huge potential, the development process demands massive amounts of data and is costly (He et al. 2024).
- **New or invasive plant diseases arise sporadically. How can digital technologies be as sensitive to these as a human expert might be?** In an increasingly globalized world, plant pathogens are known to be unwitting passengers between regions, and early detection and management can be crucial to successful eradication (Oerke 2020). Prominent examples are citrus greening disease in the United States, quick olive decline syndrome in Italy, and syndrome basses richesses of sugar beet in Germany (Sankaran et al. 2013; Zarco-Tejada et al. 2018). Can digital technologies rise to this challenge, and do we need a global library of digital disease signatures?
- **What are the requirements to enable accurate and reliable identification and quantification of multiple stressors and/or multiple diseases at once?** Sensors and associated digital technologies must be capable of discerning a range of diseases on different varieties or cultivars of the same host crop species. Whereas a human expert can readily and rapidly differentiate causes, digital sensors have not yet been sufficiently challenged or tested. This is an area of research that needs urgent attention.
- **Regarding the use of digital technologies for disease management, what is the effect of spot application on disease control and the subsequent epidemic development and disease dynamics?** Has the disease already spread? If it is identified in a particular area, does a buffer area need to be treated, and if so, to what distance? Further research is needed to perform and evaluate site-specific pesticide applications. Research to develop approaches for effective "spot" disease management and to determine the benefit to the environment and biodiversity is needed. Recent developments integrated not only optical sensors on UAVs for disease detection but also fungicide applications using spray drones. In addition to clarifying the regulatory framework, the performance and precision of such approaches need to be investigated.
- **What does site-specific application of a pesticide mean for registration routines and risk assessment, and can digital technologies be reconciled with national regulations such as control thresholds?** Registration of pesticides is a costly and complex process; several authorities are involved. The current registration routine focuses on the application of the product to entire fields. Toxicity and harmful effects are evaluated and considered. With digital technologies, site-specific applications become feasible, and risks and harmful effects may be reduced (Rajmis et al. 2022). How can this be incorporated into registration routines? How is the persistence and distribution of plant protection compounds affected by site-specific application? National regulations such as control thresholds are a central part of IPM. New, sensor-based approaches need to be able to perform accurate assessment of control thresholds.
- **How should the digital technologies eventually be transferred to the end users? Should the systems themselves be available, or should they be provided as a service through crop management consultants or advisory services?** This is a complex topic that depends on the technology being transferred (Giua et al. 2022; Steinke et al. 2021; Storm et al. 2024). Simple applications such as smartphone apps can be easily transferred. The more complex the technology, the more careful its

introduction must be, and the more expert knowledge is required. Intellectual property laws may be applicable. Furthermore, if a user does not apply the technology properly, the result could be substantial crop losses, which can increase the resistance to the uptake of the technology. Legal action may be implemented against the purveyor of the digital technology. The cost for digital technology could be relatively high, the technologies have complex routines, and users are generally highly trained individuals. Will the technology eventually be packaged in an easy-to-use system and be economically feasible?

- **Classical university degrees and education do not include classes on sensors, robotic or machine learning, and their application or implementation in crop science. How should the training of students, farmers, and consultants be developed?** The basics of digital technologies in the plant sciences must be integrated into current degree programs, training courses, and vocational training. In addition to theoretical principles, it is also necessary to teach practical skills—from recording sensor data to agronomic interpretation and decision-making. Because technologies develop fast and innovations enter the market, a regular learning program must be offered to keep practitioners updated (Klerkx et al. 2019; Pogorelskaia and Várallyai 2020).

Conclusion

Noninvasive digital technologies for the detection and quantification of plant diseases, including sensors, robotics, and machine learning, have improved dramatically recently. The incorporation of these technologies into disease monitoring is advancing, although their accuracy is still affected by various factors, such as the target's characteristics, sensor operation scales, and the environment. Although transferring research to practical application faces hurdles, digitalization promises to enhance IPM and align with policy and environmental goals. Digitalization will help to further develop and advance IPM, making it an increasingly effective approach for disease management in the future. Human expertise, particularly that of scientists and farmers, remains crucial in this technological evolution.

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