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Digital plant protection

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Abstract. *Over the last twenty years, the process of digitization has increasingly entered agriculture, including plant protection. This study summarizes research on various aspects of digital plant protection, mainly in relation to diseases and insect pests. It examines the possibilities of digitization in terms of forecasting, identification, monitoring and application of plant protection products, comparing them with classical methods used in phytopathology and entomology. Attention is paid to Integrated Pest Management, Decision Support Systems, forecasting models, remote sensing systems and Artificial Intelligence as well as their features.*

Keywords: plant protection, digitalization, monitoring, identification, forecasting

Crop production and plant protection are facing multiple challenges worldwide today. According to Mahlein et al. (2024) crop science and agricultural practice are caught between sustainable productivity gains, changing environmental conditions, and changing policy frameworks. Plant protection, as part of the technological process, is being drastically re-examined and changed to protect the environment and people in order to meet the standards of “green agricultural development” (Davies and Shen, 2020; Kuska et al., 2022).

Biotic stress caused by diseases, pests and weeds is the great enemy of crop growth, appearing throughout the growing season, reducing the quantity and quality of the yield (Martinelli et al., 2015; Kaivosoja et al., 2021). The use of pesticides can significantly reduce losses in agriculture, but it carries the risk of mutagenic, carcinogenic and teratogenic effects on higher animals and human, pesticide residues in plant production, environmental pollution and other negative effects (Wang et al., 2022).

The term Integrated Pest Management (IPM) was coined in the late 1960s to refer to practices for the synergistic management of plant pests and diseases based on ecological and economic principles (Kogan, 1998; Wallhead and Zhu, 2017). IPM aims to utilize agronomic measures for disease and pest control: cultivation of resistant varieties, crop rotation, biological or conventional chemical-based plant protection, reductions in synthetic pesticide use (Mahlein et al., 2024). According to Savary et al. (2019) IPM has reduced yield losses in five major food crops (i.e. wheat, rice, maize, potatoes, soybeans) by 20–40%, which caused by plant pathogens and pests. According to Deguine et al. (2021) high demands and expectations were placed on this concept but were not fully met in agricultural practice. Hundreds of definitions of IPM exist all over the world which are mostly misunderstood by farmers (Mahlein et al., 2024).

The implementation of IPM in Europe is regulated by Directive 128/ 2009/EC on the Sustainable Use of Pesticides, which establishes an action framework for the reduction of pesticide load and related impacts on human health and the environment. This Directive requires each Member State to develop a National Action Plan (NAP), where a DSS for plant disease and insect management needs to be an integral part of the decision-making process. A recent strategic position paper, the European Green Deal with the Farm to Fork (F2F) Strategy, describes aims to reduce the number of conven-tional pesticides applied to crops by 50% by 2030 and to promote organic production (Purnhagen et al., 2021; Mahlein et al., 2024).

Applying IPM principles requires accurate methods for identification, quantification of insects and diseases and informed decisions to identify the most appropriate control measures (Deguine et al., 2021). These can be achieved by using standard, classic plant protection methods (phytopathologycal and entomological) or modern, digital plant protection.

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The aim of this work is to examine the possibilities for digital plant protection, specifically for diseases and insects.

At the beginning, it is necessary to define some terms related to digitalization, which are often used and sometimes wrongly considered as synonymous:

- Precision agriculture (PA) - a modern farming approach that utilizes technologies such as GPS, sensors, and satellite imaging to optimize agricultural practices (U.S. Government Accountability Office, 2024).
- Artificial Intelligence (AI) - technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity, and autonomy. It involves building systems capable of performing tasks that required human intelligence, such as making decisions, and identifying patterns (Coursera Staff, 2024).
- Machine learning (ML) - a subfield of AL that uses algorithms trained on data sets to create models that enable machines to perform tasks that would otherwise only be possible for humans. It is a method of data analysis that automates analytical model building (Coursera Staff, 2025a).
- Internet of things (IoT) - a network of physical devices, vehicles, appliances, and other objects embedded with sensors, software, and network connectivity, enabling them to collect and exchange data (IBM, 2023).
- Digital twins (DT) - virtual replicas of physical objects or systems that serve various purposes (Coursera Staff, 2025b).
- Remote sensing - acquisition of information about an object or phenomenon without making physical contact with the object. It generally refers to the use of satellite- or aircraft-based sensor technologies to detect and classify objects (Liu and Mason, 2009).

Since the beginning of the 21st century, technologies in the agricultural sector have developed extremely rapidly. This has enabled a complete metamorphosis in plant protection. Digital plant protection provides opportunities in four very important areas: forecasting, identification/detection, monitoring, and application of plant protection products (PPPs), which are interconnected. Mahlein et al. (2024) determined the digital technologies in crop protection as a nascent, emerging toolbox with great potential to contribute to today's challenges and demands.

Predicting conditions that warrant intervention is considered a key principle of the concept of IPM, with the use of expert systems and dynamic crop-pest models (Kogan, 1998). Plant disease is a result of interaction between the plant, pathogen and environment. Insect life cycle is also strongly dependable on the environment. According to Wallhead and Zhu (2017) the use of meteorological data is considered a key element of modern Decision-support systems (DSS) and aid in site-specific management recommendations and farmers are encouraged to have at least one weather-monitoring station for each unique management site.

Decision-support systems are tools, interactive computer-based systems, that help growers to decide which management options to employ to control plant diseases and insect pests by utilizing data and models to solve problems under complex conditions (Magarey et al., 2002, Shtienberg, 2013). In the context of digital plant protection they can be used for forecasting and optimal timing of application of PPPs, more precisely, reduce pesticide use, and/or to improve disease and insect control (Gent et al., 2013, Morgan et al., 2000, Trapman, 2016, Wallhead and Zhu, 2017). Effective DSSs are required to provide agricultural practitioners with advice regarding appropriate and economic pest management strategies (Duffy et al., 2017) and to complement recent changes regarding pesticide regulations in the European Union aimed at a general reduction of pesticide applications (Lechenet et al., 2017). In practice, however, successful decision making depends upon the availability of integrated, high-quality information (Harrington and Hulle, 2017) and the information-base should be ensured continuously and in high resolution by extensive monitoring. A major problem with Farmer Support Systems (FSS) is that farmers do not want to be offered one possible action in a specific situation, but several possible solutions, and to make their own decision according to the circumstances. Another problem with using these systems, and in general with all the opportunities that digital farming offers, is the often lack of trust on the part of farmers in the various products. According to Magarey et al. (2002) delivering simple

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and complex DSSs provides a “pathway of learning” for farmers to progress from one level of complexity to the next.

DSS for pesticide use reduction and according to the IPM concept, have been implemented for many years with varying degrees of acceptance by farmers (Shtienberg, 2013). The integration of DSS and expert systems can allow for automated spraying using variable-rate sprayers or fixed-rate spray systems, which allows for potential reductions in spray volume up to 68% and drift reduction (Zhu et al. 2017; Wallhead and Zhu, 2017).

Forecasting models of disease infection and insect risk are essential components of DSS for plant protection, which are increasingly in demand by farmers (Cunniffe et al., 2015). They must be based on the biology and ecology of the pests concerned (Prasad and Prabhakar, 2012) and pathogenesis and epidemiology of plant diseases. There are many examples of operational DSSs with plant disease and/or insect modules: 70 disease models are listed by Campbell and Madden (1990), 11 by Travis and Latin (1991), several aphid forecasting models (Batz et al., 2023), five insect models (Dalal and Singh, 2017), etc.

In insect pests models often simulate one or a few species and rely on the most complete information possible on the auto-ecological demands of the developmental stages which respond to the prevailing environmental conditions (Batz et al., 2023). Chen et al. (2022) proposed a prediction model that combines IoT technology with long and short-term memory networks (LSTM). It can predict the occurrence and distribution of litchi stink bugs in the future based on historical data, including meteorological factors and pest survey. According to the authors it is critical to help farmers take up crop protection and pest control measures to prevent damage to the yields. They noticed that the use of environmental sensing data based on LSTM can not only forecast meteorological conditions but can also fill in the missing values of historical data. According to them incorporating environmental data with pest surveys, machine learning technology can be used to predict the correlation between environmental factors, such as temperature, humidity, and light, and pest incidence.

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 (Mahlein at al., 2024). Many authors investigated and reviewed the principles of decision support or early warning systems in different pathosystems (Bregaglio et al., 2022; Dong et al. 2020). According to Ojiambo et al. (2017) data from several years and differing environments are required to develop and validate such models. Farmers can use DSSs that integrate prediction models to optimize crop protection and maximize yield (Hughes, 2017). Rossi et al. (2019) noticed that the use of DSSs has been restricted to certain geographic areas and crops and a limited group of users, mainly in developed countries. According to Lucas et al. (2015) the dynamics of plant pathosystems are complex, influenced by genetic and environmental factors, and challenged by the evolution of host–pathogen interactions. 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 on the environment and thus affect social and ethical aspects of crop production (Klerkx et al., 2019; Lajoie-O’Malley et al., 2020; Mahlein at al., 2024).

According to Batz et al. (2023) monitoring and forecasting models are by their nature related, as forecasting models almost always rely, at least partly, on data derived from monitoring activities. Identification and detection of plant diseases and insect pests are probably the most important factors for success in digital or conventional plant protection.

Insects are identified by various morphological characteristics of the body at different stages of their development using specialized differentiation keys. Their correct identification requires in-depth knowledge of the anatomy and morphology of the insect body and is often subject to human error.

Insects are monitored via established sampling methods including trapping, sweep netting, and portable aspiration (Burkholder and Ma, 1985). Insect identification has been automated as early as 1973 using wingbeat frequency (Reed et al.,1942; Moore et al., 1986). Today, insect monitoring includes acoustic detection (Mankin et al., 2011), radar observations (Drake et al., 2020), and lidar (Brydegaard and Jansson, 2018).

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Trapping methods monitor insects landing, walking, or jumping to a specific point and do not record insects in flight. Also, each trapping method is biased towards different insects, with the trap color influencing the trap catch (Rydhmer et al., 2022).

According to Noskov et al. (2021) insect trapping, and in particular light trapping, are major methods of insect monitoring with a long history and a large body of relevant scientific publications and reviews. The authors noticed that researchers often combine light traps with cameras and use computer vision, AL, and ML algorithms to process the data.

Sweep netting is probably the most similar monitoring method, as it also captures insects in flight over the crop. However, net trapping, which also collects insects on plants, is performed at a measurement point in time and is usually performed along a transect rather than at a fixed point in the field (Binns and Nyrop, 1992). Also, each trapping method targets different insects, which affects the catch (Bannerman et al., 2015). Insect capture methods, such as the water traps used in this study, observe insects landing, walking, or jumping to a specific point and do not record insects in flight. Also, each insect capture method targets different insects, with trap color influencing capture (Rydhmer et al., 2022).

Insect radar was developed over 70 years ago (Noskov et al., 2021). According to Abd El-Ghany et al. (2020) the types of radars are: airborne (AER), scanning (SER), tracking (TER), and vertically oriented (VLR) entomological radar systems. VLR was developed in the 1990s to track the population dynamics of migratory insect species for entomological purposes (Hobbs, 1991; Perry et al., 1993). FMCW (frequency modulated continuous wave radar) is another type of radar, which is used to study layers in the atmosphere, and insects appear as discrete points in the resulting diagrams (Metcalf, 1975; Eaton et al., 1995; Noskov et al., 2021). According to Rydhmer et al. (2022) radar technologies are unsuitable for monitoring small insects or insects around vegetation, such as crop crowns.

Lidar (Light Detection and Ranging) can be used to record many observations over a long transect (Fristrup et al., 2018) and to distinguish between species groups by wingbeat frequency (WBF) (Jansson et al., 2021). However, lidar equipment requires a trained operator and constant monitoring due to eye safety limitations (Rydhmer et al., 2022). According to Noskov et al. (2021) lidar devices show promising potential in the high-resolution remote sensing entomology.

In classical phytopathology plant diseases are monitored by visual inspection, regularly in the field. Plant pathogens cause anatomical and morphological changes in the diseased plant, resulting in various symptoms. Macroscopic diagnosis is often very difficult due to the similarity of symptoms caused by abiotic and biotic stress. In this case, various laboratory methods are used: physiological, biological, serological, and molecular tests (Gullino and Bonants, 2014). The most common laboratory tests over the last twenty years have been serological tests, such as enzyme-linked immunosorbent assay (ELISA), based on the use of proteins in the detection of disease agents, as well as molecular tests, such as polymerase chain reaction (PCR), used to detect plant diseases, based on the DNA sequence of the pathogen (Fang and Ramasamy, 2015). The use of these methods requires special equipment, consumables, and manual labor, which is why they are mainly used in scientific research rather than practical needs.

In many pathosystems early detection of diseases is very important to avoid yield losses by timely applications of foliar fungicides. According to Nwauzoma (2016) rapid diagnosis of plant pathogens is also critical because some fungicides cannot be applied after a certain stage in plant's maturity.

Khaled et al. (2017) mentioned many non-invasive techniques for disease detection such as: terrestrial laser scanning, image processing, electronic nose, sonic tomography, microfocus x-ray fluorescence (uXRF), GanoSken technology and spectroscopy. Based on their mode of application, the authors divided the spectroscopy techniques into molecular (visible (VIS), infrared (IR), nuclear magnetic resonance (NMR), mass spectroscopy (MS) and electrical impedance (EI)) and atomic (fluorescence spectroscopy (FS)).

Spectroscopy is the study of the interaction of electromagnetic waves including ultraviolet (UV), visible, and infrared (IR) spectra with matter, in our case the plants (Willets and Van Duyne, 2007). As a result of pathological processes, physiological and biochemical changes occur in the plant, which lead to reduced chlorophyll content, impaired cell structure, reduced intensity of photosynthesis, transpiration, stomatal conductance, reduced moisture levels and leaf pigmentation, and dry matter accumulation. All this leads to distinctive changes in the spectral reflectance of infected leaves, which makes them detectable by spectroradiometry and remote sensing techniques (Ganeva et al., 2024). Results of many

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investigations confirm and demonstrate the use of this method for detection of plant disease under greenhouse and field conditions in many crops as: cereals (Atanasov et al., 2022; Ren et al., 2021; Ganeva et al., 2024; Heidarian et al., 2020; Bauriegel and Herppich, 2014), orchards (Abu-khalaf and Salman, 2014; López-López et al., 2016), etc.

Remote sensing is the use of non-contact, often optical sensors such as red-green-blue (RGB) (Görlich et al., 2021), multi- and hyperspectral (Thomas et al., 2018), thermal, chlorophyll fluorescence, and 3D-imaging (Paulus, 2019), to obtain information about processes occurring in the field (Mahlein, 2016; Mahlein et al., 2024). Technology uses high-resolution spectral imaging through satellites, planes, and unmanned aerial vehicles (Qin et al., 2023) which enable the real-time, non-invasive assessment of plant vigor and the detection of diseases (Mahlein, 2016; Abbas et al., 2023). The integration of these sensors in agricultural ecosystems will give more detailed light on the crop–climate–disease interaction (Arshad et al., 2023; González-Rodríguez et al., 2024).

In Bulgaria scientific publications on the use of any kind of digital technologies in plant protection, including phytopathology and entomology, are limited. Most of them use NDVI (Normalized difference vegetation index) to monitor some diseases such as yellow rust, brown rust and leaf spots in wheat (Atanasov et al., 2022; Ganeva et al., 2024). Koleva et al. (unpublished data) established a correlation between the values NDVI, chlorophyll content in leaves and the disease intensity in four pathosystems: common bean – *Uromyces appendiculatus* (Pers.:Pers.) Unger., tomato - *Alternaria* sp., winter wheat – *Blumeria graminis* f. sp. *tritici* (DC.) Speer. and winter wheat – *Puccinia triticina* Erikss. The authorts determined changes in NDVI due to abiotic factors, such as nitrogen deficit and following fertilization. They confirm the thesis of Cabrera-Bosquet et al. (2011) that NDVI can be used as a signal for changes in plants, but not as a diagnostic tool.

Based on innovations in different areas of digitalization in the agricultural sector smart plant protection or digital plant protection is under development and is prioritized by several corporations in the agricultural sector (Sawant et al., 2023). In their work Sawant et al. (2023) notes that integrating AI into DSS, creating DSS platforms, greatly facilitates effective disease control. These DSS platforms consider factors such as weather conditions, crop phenology, and disease distribution, and offer personalized recommendations to farmers in real time on disease control strategies, optimal pesticide use, based on AI-generated analyses (Hu et al., 2023; Sawant et al., 2023; Banerjee and Mondal, 2023; Koleva et al., 2024). These platforms, based on models discern subtle multivariate relationships, predict disease outbreak risks, and enable targeted intervention strategies undetectable via conventional approaches (Banerjee and Mondal, 2023; Gonzales-Rodrigez et al., 2024).

Artificial intelligence (AI) offers new opportunities to decipher the complexity of plant pathosystems and derive practical knowledge for disease management (Singh et al., 2016; Zhao et al., 2023). Gonzales-Rodrigez et al. (2024) made a review about the application of AI in Phytopathology. According to the authors, artificial intelligence (AI) allows for: rapid and precise detection and automatic diagnosis of diseases, overcoming the limitations of techniques relying on visual inspection; provides opportunities for prediction of the occurrence and development of various pathosystems (cereals and grapevines) up to 3 weeks prior at 81–95% precision. According to Tummapudi et al. (2023), ML models that integrate weather, soil, and crop data are becoming increasingly advanced, helping farmers make well-informed decisions about key stages of the technological process such as irrigation, fertilization, and harvesting.

Mahlein et al. (2024) conclude that there are several challenges to developing and transferring existing digital technologies to function accurately in all area of plant production and plant protection. They can be summarized as: the existing models and approaches often cannot be generalized among different environments; sensor settings may need adjustment even among cultivars within a crop; limited information about assessment of disease incidence or disease severity using digital tools, which can contribute to reduction of the amounts of pesticides applie by spot-spraying capability; the system must be sensitive enough to assess thresholds value correlated with disease incidence or disease severity. According the authors digital technologies can be integrated with IPM by substituting some of current methods. Disease detection before symptom development, during incubation period, has been demonstrated in laboratory conditions, but according to Mahlein et al. (2024) it is not clearly how can this technology be transferred effectively to the field.

Now a days, management decisions for disease and insect pest control rely only on conventional, classical methods or combination of them and digital monitoring and prediction systems based on

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weather data and epidemiological parameters of plant diseases and insect pests (Ristaino et al. 2021; Mahlein et al., 2024). The huge amount of different crops, different varieties, phenophases, climates, soil conditions, and pathogen strains pose challenges in creating AI tools with sufficient flexibility for in situ usage (Singh et al., 2016; Singh et al., 2018; Gonzales-Rodrigez et al., 2024). Kuska et al. (2022) mentioned that generalized frameworks and models are necessary, which are intuitive and accessible for the farmer which indicate that a global database with spectral disease and plant spectra, could be a great foundation.

Digitalization is called the "fourth revolution" in agricultural sector (Knierim et al., 2019). From a practical point of view it is useful for farmers, especially in the field of plant protection. Many authors consider that digital plant protection will change and improve farmers' knowledge, skills and work (Klerkx et al. 2019; Zolkin et al. 2021) and will give new, different insight of the complex interaction between plants, environment and plant diseases and insect pests.

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