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DIGITALIZATION IN PLANT PRODUCTION AND PLANT PROTECTION IN BULGARIA – CURRENT STATUS AND FUTURE GOALS

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Abstract

According to the "Strategic Plan for the Development of Agriculture and Rural Areas of the Republic of Bulgaria for the period 2023-2027", Bulgaria is significantly behind the other EU members in terms of digital technologies, especially in agriculture. The present study aimed to follow the historical development of agriculture up to the so-called “fourth revolution” - Digital agriculture (DA). DA can be considered from a scientific and practical point of view. Science can demonstrate and prove the benefits of using a given tool or software by comparing the results with those obtained using standard analysis methods. From the users' point of view, the product must be easy to use, accessible from a technical and economic point of view and, most importantly, provide accurate information. Many investigations on DA are made in Bulgaria, but most of them study it economically. Farmers have access to a variety of DA products, but unfortunately research shows that a small percentage of them use them. Although only 14% of farmers apply modern digital technologies, there is a trend towards increasing their interest in DA, which will accelerate in the future.

Key words*: *digitalization, agriculture, plant production, plant protection

In the last century, agriculture has gone through several periods of development: industrial, green revolution, sustainable development, and today we are witnessing the period of digitalization (Nikolov et al., 2022).

The first period began after the Second World War and was characterized by agrotechnical measures with a significant degree of mechanization, and traditional varieties of plants were replaced by those with high productive potential (Stoynev, 2004). During this period, synthetic plant protection products (PPPs) began to be applied more and more in plant production. As a result, many negative effects on the state of the entire ecosystem begin to appear, mostly related to the pollution of soil, air, water and production (Nikolov et al., 2022).

Norman Borlaug started the green revolution in the middle of the 20-th century (Patel, 2012). During this period, new practices related to cultivation technology, use of resistant varieties and mineral fertilizers, PPPs were created and used, while at the same time agricultural technology was improved. As a result, an increase in the quantity and quality of yield is achieved in crops that are essential for feeding the population (Patel, 2012; Slavova, 2022).

The term “sustainable agriculture” is derived from the concept of 'sustainable development' and is characterized as ecologically, economically and socially vibrant, harmonious and balanced development (WCED, 1987). According to Nikolov et al. (2022) the sustainability of agricultural production defines the ability of agricultural systems to develop at a stable pace, adapting to ongoing changes in time and space.

The process of digitization and introduction of technological solutions in agriculture is not new. It began in the late 1980s in the USA and Australia with the development of the Global Positioning System (GPS), Geographic Information Systems (GIS), remote sensing, simulation modeling and the formulation of the concept of "Precision agriculture" (PA) (Beznosov at al., 2019; Stafford, 2000). The use of these systems leads to increased yields, the efficiency of the application of fertilizers and PPPs, reduces the agrochemical influence on the environment and significantly improves the quality of the crop (Beznosov at al., 2019).

The first definition of PA was given in 1997 as "an integrated farming system based on the use of digital information, aiming to increase the long-term efficiency of farm production as well as its productivity, while minimizing negative impacts on the environment" (Nikolov et al., 2022). According to Gebbers and Adamchuk (2010), PA is a way of “applying the right treatment to the right place at the right time” and Goedde at al. (2020) determined PA as a technological approach that monitors, measures and analyzes the needs of individual fields and crops.

The application of PA is possible because of the development of sensor technologies. These sensor devices are designed both for recording data about positioning and for recording data about movement and location of both machines and equipment as well as personnel employed in production (Nikolov et al., 2022). There are sensor devices for soil condition assessment, such as apparent electrical conductivity (ECa) sensors, gamma radiometric soil sensors and soil moisture tracking devices, management of agrotechnical activities such as cultivation, sowing, fertilization, application of PPPs, harvesting, etc. Other sensors record weather information or microclimate data. Particular importance is given to sensors developed to quantify the physiological status of agricultural crops. These sensors are based on principles of remote sensing and detection of different wavelengths, using multispectral and hyperspectral cameras on board airborne and satellite platforms, aiming to determine vegetation index that show the condition of agricultural crops (e.g. content of chlorophyll, stress level) and its variability in space and time (Nikolov at al., 2022).

Another important element is the use of Controlled Traffic Farming (CTF), Variable Rate Application (VRA) and Variable Rate Technology (VRT), which enables precision seeding, optimization of planting density and improved efficiency of application of herbicides, pesticides and fertilizers to crops, resulting in a reduction on-farm costs as well as reducing the impact on the environment (Nikolov at al., 2022).

Precision agriculture is applied in all branches of agricultural production: field crops, vegetables, orchards and viticulture (Njoroge et al., 2002; Mihaylov et al., 2020). Later, the concept of "smart agriculture" appeared. It differs from PA in that it focuses primarily on access to and use of analytical and digital data (Yordanov, 2020). Gradually, this phase of precise and intelligent development led to the appearance of "digital agriculture" (DA) in 2010 in America and Western Europe (Slavova, 2022). According to Knierim et al. (2019) DA is considered the “fourth revolution” in this sector.

According to the German Agricultural Society, digital agriculture is "creating value from data" (Slavova, 2022). DA uses the possibilities of precision agriculture, but also includes smart networks and data management tools, and its main goal is to use available information and experience to make possible the automation of sustainable processes in the sector (Skvortsov, 2019). Digitization, by its nature, represents a process of conversion (transformation) of information on an analog medium (text, sound and video signals, telephone pulses, etc.) in digital form. This is done through electronic devices using the scanning method, which includes the very processes of converting analog data into digital. This allows information to be processed, stored and transmitted in a digital environment through computer networks, satellite, internet, social networks, etc. (Nikolov et al., 2022).

Many authors classified digital technologies in agriculture 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; Mahlein et al. 2024).

According to Kovács and Husti (2018), agriculture can significantly increase its efficiency and competitiveness by taking advantage of digitization. The digitization of the sector enables using GPS services, machine-to-machine (M2M) and Internet of Things (IoT) technologies, sensors and big data, 3D printing, system integration, ubiquitous connectivity, artificial intelligence, machine learning, digital twins and blockchain among other algorithms and technologies to optimize crop yields and reduce environmental waste. Precision agriculture and digitization are today perceived as a panacea that can deal with the increasing pressure on ecosystems that agriculture generates (Nikolov et al., 2022).

According to Rupnik et al. (2019) we are in the era of making PA omnipresent, whilst trying to enrich it with computer-assisted Decision Support Systems (DSS) for entire farm management.

Hundreds of DSSs have been developed over the years and are available. They use scientific knowledge that can help farmers make farm management decisions. Agricultural DSSs are software applications, usually based on computer models, that describe different biophysical processes in agricultural systems and how they respond to different management practices (eg irrigation, fertilizers, sowing and harvesting dates) and/or climate variability (eg. temperature and rainfall) (McCown, 2002; Jakku and Thorburn, 2010). DSSs can support crop management, optimize nitrogen fertilizer management, or assess the impact of seasonal climate variability on crop production (Zhai et al., 2020, Jakku and Thorburn, 2010).

One of the most important applications of DSSs is in plant protection. They can be successfully used in three directions: identification, forecasting and PPPs application.

DSSs help in the management of plant diseases and insect pests by utilizing data and models to solve problems under complex and uncertain conditions (Magarey et al. 2002, Shtienberg 2013; Wallhead and Zhu, 2017). DSS can be implemented to reduce pesticide use, and/or to improve disease and insect control (Morgan et al. 2000). According to Gleason (1997) DSSs can reduce pesticide use substantially compared with traditional, calendar-based spray schedules with no added risk of yield. The integration of DSS and expert systems can allow for automated spraying through use of variable-rate sprayers or fixed-spray systems, allowing for potential reductions in spray volume and drift reduction. That has the capacity to reduce average pesticide use by up to 68%, which results in an annual average cost savings (Zhu et al., 2017). In situations where variable-rate spraying is not an option, optimal application timing of spray materials can be achieved while conserving resources (Wallhead and Zhu, 2017).

DSSs can be very useful tool in Integrated Pest Management (IPM), even though most farmers do not use them as part of their IPM practices (Shtienberg, 2013).

The Directive 128/ 2009/EC promoted IPM in Europe. This Directive requires each Member State to develop a National Action Plan (NAP), where a DSS for plant disease management needs to be an integral part of the decision- making process (Bregaglioa, 2022). 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 (Purnhagen, 2021).

Yield loss due to pathogens and insects is a major concern in agriculture, requiring the need for advanced disease and insect detection and prevention measures to minimize the damage of plants (Dong et al., 2021). Novel bioinformatic tools have opened doors for the low-cost rapid identification of pathogens and insects and prevention of disease. The number of these tools is growing fast and according to Dong et al. (2021) a comprehensive and comparative summary of these resources is currently lacking.

In 1927, Neblette showed that aerial photography (RGB) enables disease survey in agricultural crops. In 1933, Bawden discovered in the lab that a black-and-white representation of an infrared photography resulted in high contrasts between necrotic leaf spots caused by potato viruses. These findings set the stage for the use of different spectral bands to detect differences in plant health (Kuska et al., 2018).

Colwell (1956) suggested to test different combinations of spectral bands for disease detection. The author remotely identified wheat rust and other diseases of grains by using infrared-filter cameras, as well as a spectrometer at oblique and nadir observation angles. He proposed a new view on the interaction of light with plants and the assessment and interpretation of crop photos for plant diseases. Colwell contributed an important theoretical framework that is still of utmost importance in digital plant pathology (Kuska et al., 2018).

In the process of detection of disease, number of imaging techniques is being used: magnetic resonance imaging, photo acoustic imaging, tomography, thermography, spectroscopic and imaging technologies, multispectral imaging, hyperspectral imaging, fluorescence techniques, thermal imaging, 3D imaging (Singh et al., 2020).

Weather-based consultation and forecasting systems (e.g., proPlant; Ag-radar; Horta; RIMPro; Skybit), enable the best plant protection measures by their warning services of appearing pests and diseases (Newe et al. 2003; Wallhead and Zhu, 2017; Kuska et al., 2018). They are based on a huge number of scientific studies on the elements of the pathogenesis: host, pathogen and environment and the interaction between them. According to Kuska et al. (2018) pathosystems can be very specific and complex, existing techniques must be critically evaluated and calibrated according to each pathosystems details. The authors proposed generalized frameworks and models to be made, which are intuitive and accessible for the farmers.

The use of these systems for identification and forecasting plant diseases has some disadvantages. In many cases abiotic and biotic stresses in plant resulted in a similar visual manifestation and for non-professional researchers, especially farmers, identifying crop diseases and pests through picture comparison or text description often leads to human judgment errors (Manavalan, 2020; Zarco-Tejada et al. 2021). The use of these systems does not exclude regular visual observations on the field but can save time and effort by the farmer.

Regardless of what tool is used for pathogen identification, it is a real challenge detection before symptoms development. Host-pathogen interaction induced changes to plant physiology, morphology, and biochemistry which can be detected both pre- and post-symptomatically (Kuska et al., 2022). Zarco-Tejada et al. (2018) pre-symptomatically detect *Xylella fastidiosa* infection in olive trees. According to Mahlein et al. (2024) presymptomatic detection is highly dependent on the individual pathosystem, its biology, and epidemiology and not every disease must be detected before symptoms are visible.

Insect pest monitoring and identification using digital tools is very difficult task. Wing beat frequency or size can be detected by entomological radar. It is a remote sensing method which can identify insect pests down to species level (Noskov et al., 2021). Many investigations search for the best way to monitor and identify insect pest by digital tools using infrared sensors, audio sensors, image-based classification (Lima et al., 2020; Rydhmer et al., 2022). Different parameters such as the wing beat frequency, mentioned above, melanization and wing to body ratio can be recorded in the field, automatically uploaded to a cloud database, and processed via machine learning (ML) and artificial intelligence (Batz et al., 2021). According to Batz et al. (2023) up to now, publications in the field of insect identification on a species level with a high degree of morphological similarity using AI methods are scarce. Probably the future will provide scientists and farmers easy method or tool which will replace conventional time-consuming, costly and prone to human errors methods (Rydhmer et al., 2022).

The digital technology can be successfully implemented in plant breeding programms. In recent years plant phenotyping is a trend in plant science and breeding using various optical sensors to capture morphological, physiological and biochemical variations in plant traits (Jangra et al. 2021; Luo et al., 2024; Visakh et al., 2024). Multispectral imaging has a variety of applications in crop phenotyping which includes monitoring of nutrient content, early detection of pests and diseases, and abiotic stress response symptoms. According to Visakh et al., (2024) screening for resistance to drought is one of the widely used application of this technology.

In terms of hardware, there are ground-monitoring platforms and air-monitoring platforms and according to Wang et al. (2022), it is also a trend to integrate them for collaborative monitoring. In recent years, large companies in the sector have been working to create platforms that combine different DSSs and create a single service that can track the entire production process from sowing to harvest, including plant protection.

According to the "Strategic plan for the development of agriculture and rural areas of the Republic of Bulgaria for the period 2023-2027", Bulgaria is significantly behind the other EU members in terms of digital technologies in the economy and society, and in recent years the country ranks 26 place in the EU according to the Integral Index for Introduction of Digital Technologies in the Economy and Society (DESI). Regarding "Implementation of digital technologies", the country is in one of the last places (FAO, 2022). In agriculture and rural areas, the implementation of these technologies lags even more than in cities and high-tech industries. According to the same Strategic Plan, the implementation of digital technologies for farm management and optimization of production and administrative processes should be stimulated and supported, which will contribute to the transformation of agriculture into a high-tech, sustainable, highly productive and attractive area. The plan identifies the need for application of digital technologies for planning the production process and management of the farm, which can be achieved by promoting investments in the digitalization of the management process of business operations and production, from the planning of agronomic operations to the supply of the production. Due to the difficulties in providing labor for agricultural production, digitization in agriculture enables the automation of work processes in order to increase the productivity of crop farms. In the Common Agricultural Policy of the EU, precision agriculture and digital technologies are already exported as priorities.

In Bulgaria, there is a lack of in-depth analyzes of the digitization of the agricultural sphere and in rural areas. The reason for this is the lack of sufficient official statistics, etc. information as well as sufficient public interest in the development of this important system (Nikolov et al., 2022).

The main obstacles to the mass use of digital technologies in Bulgaria are related to a lack of specialized knowledge and skills in the field of information technologies, a lack of sufficiently well-qualified labor, a lack of awareness of the need for the implementation of digital agriculture and sufficient motivation on the part of medium and smaller farmers, as well as a lack of sufficient financial means to implement digitized processes in agriculture (Slavova, 2022).

Agriculture in Bulgaria is very diverse. The total number of registered farmers in 2021 was 76,372, and the total number of agricultural holdings was 132,742 (MAF, 2024). In general, there is a large difference between the production and management approaches applied on large and small farms. The size of the farms and the digital technologies they use are often related to the potential of the farmer to make investments and successfully grow his business. Larger farms have easier access to finance and can very quickly implement the digital farming approach, as long as they see a sense or motive to do so. For smaller farms, digitization does not create opportunities, on the contrary, it requires additional investments that are too much for them. For example, most hardware systems are compatible with specific brands of farm machinery due to purchased access to the specific patent (Nikolov et al., 2022).

According to Nikolov et al. (2022) the main challenges to digitization in Bulgaria are that it is still an expensive and inaccessible technology especially for the small farmer. Digitization requires specific skills on the part of the farmer (especially older and conservative farmers) to help him take advantage of digital technologies. The wide variety of digital solutions confuses the user and generates additional costs from hidden fees for the use of software or subsequent access to cloud services. Despite the mentioned challenges, according to the authors, the main contribution of digitalization is indisputable, related to ensuring full control over the business processes that take place in agriculture.

Digital agriculture can be considered from a scientific and practical point of view. Science can demonstrate and prove the benefits of using a given tool or software by comparing the results with those obtained using standard analysis methods. From the users' point of view, the product used must be easy to use, accessible from a technical and economic point of view and, most importantly, provide accurate information.

A bibliographic reference in the international database of scientific information Scopus finds over 3,000 sources related to digital technologies in agriculture, of which only 14 have Bulgarian authors. The Web of Science database provides access to over 24,000 sources, 99 of which have Bulgarian authors. Over 2,000 publications in both databases are related to the use of digital technologies in the diagnosis of plant diseases and pests, as well as forecasting models in the most economically important of these.

A review of studies and publications in Bulgaria shows that most of them study the use of digital technologies in agriculture from an economic and/or technical perspective. Research on the use of digital technologies directly in various branches of the agricultural sector (plant breeding, fruit growing, viticulture, vegetable production and plant protection) in the country is very limited. Most of the studies study the use of a specific digital tool (drone, camera, satellite photo) during distinct phenophases of culture development (Atanasova et al., 2021; Avetisyan at al., 2021; Ganeva et al., 2024; Mihajlow and Ivanova, 2019; Mihaylov et al., 2020; Stefanova and

Arnaudova, 2020), some basic parameters of soil quality (Georgieva et al., 2020) and its contamination with heavy metals (Ganchev et al., 2023), vegetation index (Atanasova et al., 2021; Atanasov et al., 2022a; Atanasov et al., 2022b), evapotranspiration (Vasileva et al., 2018), plant response to water deficit (Avetisyan et al., 2020). Scientific pappers regarding the use of digital technologies in disease and pest identification, disease intensity and insect density determination are very limited. Atanasov et al. (2022a) used NDVI (Normalized difference vegetation index) and demonstrated its variation in wheat yellow rust disease, with the causative agent of the basidiomycete fungus *Puccinia stiiformis* Westend. Atanasov et al. (2022) found a significant decrease in NDVI values in phenophase heading and grain filling as a result of disease development. According to Cabrera-Bosquet et al. (2011) NDVI allows a qualitative assessment and is used as an indicator, a signal, for the occurrence of changes, but does not provide a diagnosis with a specific status.

Ganeva et al. (2024) established winter durum wheat disease (yellow rust, brown rust, leaf spots) severity detection with field spectroscopy in phenotyping experiment at leaf and canopy level. According to the authors further multidisciplinary research is crucial, alongside standardized data collection methods, to unlock the full potential of spectral disease detection.

In Bulgaria, several companies offer products for DA. Most of the products on the market are oriented towards precise utilization of agricultural machinery and digital management of agricultural holdings. They can be divided into three categories: equipment; software and services.

Digital equipment includes different systems for navigation, precision planting and spraying systems, drones, unmanned ground vehicles, weather stations, precision processing systems, handheld GPS devices, agro management systems.

The agronomic services are mostly aimed at determining nutrients in the soil. The service is aimed at sampling, in most cases with specialized equipment and an automatic probe. After a soil analysis, the user is provided with a digital agrochemical map, as well as information on nutrient elements and soil pH with a recommendation for fertilization according to the crop. Digital maps may also be available to farmers by using satellite data.

The software products available on the market are very diverse. Most of them provide digital capabilities for managing the agricultural holding from an administrative point of view, tracking and analyzing data from agricultural machines, weather stations, etc.

Probably the most frequently used product in this category are weather stations. They provide valuable information on basic abiotic factors that are extremely important for any crop such as: air and soil temperature, amount of rainfall, air humidity, wind speed, sum of effective temperatures, etc. Some weather stations combine meteorological data with plant protection using DSSs for economically important diseases of a given crop. Meteo data from the weather station is automatically processed by computer models, and the farmer receives a forecast of the disease risk of the crop.

Several DSSs are available on the market in the country at the moment. They provide access to forecasting models of diseases and insects in many crops: cereals, orchards, vegetables, grapevine. The use of these systems enables the timely application of PPPs, consistent with the phenophase of crop development and weather conditions. They are based on many years of research on individual host-pathogen systems. They are easy to use, saving farmers time and money.

A foreign company provide in the country a system for Precision agriculture which combine all opportunities described above.

The system analyzes and combines data from different types of satellite systems (about 10 satellites): optical, radar and meteorological, and also integrates the results of aerial photography. They make high resolution images (from 30m and 15m per 1 pixel to 3m per 1 pixel) which are updated daily. Satellites take pictures in different spectral ranges, red and infrared, and with different resolutions. The system automatically analyzes images and calculates the vegetation index of plants (NDVI) based on the amount of chlorophyll, providing the result in the form of electronic vegetation maps, graphs and charts. The product provides personal information for each of the farm's fields regarding: meteorological data, the dynamics of the main indicators of soil quality; weather forecast for each field; yield forecast. Using the system, the farmer can observe the main indicators of a given field more than 20 years back, even if he did not farm it. The product provides a great database for insect, diseases and weeds regarding their morphology, biology, developmental features and plant protection pratices (Cropwise™, Syngenta®).

The review made in the present study on the development of DA around the world and in Bulgaria shows that the so-called the "fourth revolution" still has a lot of potential to unfold and challenges to overcome, both in the field of plant production and plant protection. Many companies are probably developing new, more sophisticated tools or improving existing ones. Although at a slower pace, digital agriculture is also developing in Bulgaria. Farmers in the country have access to a variety of digital tools to successfully use on their farms. Although, according to Bashev (2020), only 14% of farmers apply modern digital technologies, there is a trend towards increasing their interest in DA, which will accelerate in the future.

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REFERENCES

Alisa, A. (2019). News what is the difference between precision, digital and smart farming, *Digital Agriculture*, 13.08.2019

Atanasov, A., Mihova, G. and Mihaylov, R. (2022a). Applicability and efficiency of remote sensing of agricultural areas. Bulgarian *Journal of Agricultural Science*, 28 (5), 933–943.

Atanasov, A., Mihaylov, R., Mihova, G. (2022b). Investigating the possibility of monitoring the drying in the upper soil layer by means of a drone in the Dobruja region. *International Conference Automatics and Informatics* (ICAI), DOI: 10.1109/ICAI55857.2022.9960060

Atanasova, D., Bozhanova, V., Biserkov, V. and Maneva, V. (2021). Distinguishing areas of organic, biodynamic and conventional farming by means of multispectral images. A pilot study. *Biotechnology & Biotechnological equipment*, 35 (1), 977–993.

Avetisyan, D., Nedkov, R., Georgiev, N. (2022). Monitoring maize (Zea Mays L.) phenology response to water deficit using Sentinel-2 multispectral data. Proceedings Volume 11524, *Eighth International Conference on Remote Sensing and Geoinformation of the Environment* (RSCy2020); 1152403 (2020) https://doi.org/10.1117/12.2570734

Avetisyan, D., Borisova, D. and Velizarova, E. (2021). Integrated Evaluation of Vegetation Drought Stress through Satellite *Remote Sensing. Forests*, 12(8): 974; https://doi.org/10.3390/f12080974

Batz, P., Will, T., Thiel, S., Ziesche, T.M., and Joachim, C. (2023). From identification to forecasting: the potential of image recognition and artificial intelligence for aphid pest monitoring. Front. Plant Sci., 14, DOI: https://doi.org/10.3389/fpls.2023.1150748.

Bashev, H. (2020). Digitalisation of Bulgarian Agriculture and Rural Areas. *Bulgarian Journal of Agricultural Economics & Management* / Ikonomika i Upravlenie na Selskoto Stopanstvo, 65, (2), p3. (Bg).

Bawden, F.C. (1933) Infra-red photography and plant virus diseases. *Nature*, 132, 168–168. https://doi.org/10.1038/132168a0

Beznosov, G.A., Skvortsov, E.A., Semin, A.N., Nekrasov K.V., Ziablitckaia, N.V., Nabokov, V.I. (2019). Economic and mathematical modeling in the system of precision agriculture. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies*, 10 (4), https://tuengr.com/V10/453.pdf

Bogue, R. (2016). Robots poised to revolutionise agriculture. *Ind. Robot*, 43: 450-456.

Bregaglioa, S., Saviana, F., Raparellia, E., Morellia, D., Epifania, R., Pietrangelib, F., Nigroc, C., Bugianid, R., Pinie, S., Culattif, P., Tognettig, D., Spannah, F., Gerardii, M., Delilloj, I., Bajoccoa, S., Fanchinia, D., Filaa, G., Ginaldia, F., Manici, L. M. (2022). A public decision support system for the assessment of plant disease infection risk shared by Italian regions. *Journal of Environmental Management*, 317: 115365. DOI: https://doi.org/10.1016/j.jenvman.2022.115365

Cabrera-Bosquet, L., Molero, G., Stellacci, A. M., Araus, J. L., Bort, J., Nogues, S. (2011). NDVI as a Potential Tool for Predicting Biomass, Plant Nitrogen Content and Growth in Wheat Genotypes Subjected to Different Water and Nitrogen Conditions. *Cereal Research Communications*, 39(1), 147-159.

Colwell, R.N. (1956) Determining the prevalence of certain cereal crop diseases by means of aerial photography. *Hilgardia*, 26, 223 286. https://doi.org/10.3733/hilg.v26n05p223

Dong, A., Wang, Z., Huang, J., Song, B., Hao, G. (2021). Bioinformatic tools support decision-making in plant disease management. *Trends in Plant Science*, 26 (9), 953-967.

FAO (2022). Strategic plan for the development of agriculture and rural areas for the program period 2023-2027. https://www.fao.org/faolex/results/details/en/c/LEX-FAOC222372/

Ganeva, D., Filchev, L., Roumenina, E., Dragov, R., Nedyalkova, S. and Bozhanova, V. (2024). Winter Durum Wheat Disease Severity Detection with Field Spectroscopy in Phenotyping Experiment at Leaf and Canopy Level. *Remote Sens*, 16, 1762. https://doi.org/10.3390/rs16101762

Gebbers, R. and Adamchuk, V. I. (2010). Precision Agriculture and Food Security, Science, 327, no. 5967, 828–831.

Georgieva, Ts., Mihaylova, A., Daskalov, P. (2020). Research of the possibilities for determination of some basic soil properties using image processing. *7th International Conference on Energy Efficiency and Agricultural Engineering* (EE&AE), DOI: 10.1109/EEAE49144.2020.9279007

Gleason, M. L., Parker, S. K., Pitblado, R. E., Latin, R. X., Speranzini, D., Hazzard, R. V., Maletta, M. J., Cowgill, Jr, W. P., and Biederstedt, D. L. (1997). Validation of a commercial system for remote estimation of wetness duration. *Plant Disease*, 81, 825–829.

Goedde, L., Katz, J., Ménard, A., and Revellat, J. (2020). Agriculture's connected future: How technology can yield new growth, McKinsey& Company, October 9, 2020. Agriculture's technology future: How connectivity can yield new growth | McKinsey.

Jakku, E., Thorburn, P.J. (2010). A conceptual framework for guiding the participatory development of agricultural decision support systems. *Agricultural Systems*, 103 (9), 675-682.

Jangra, S., Chaudhary, V., Yadav, R. C., and Yadav, N. R. (2021). "High-Throughput Phenotyping: A Platform to Accelerate Crop Improvement." *Phenomics*, 1 (2), 31–53. https://doi.org/10.1007/s43657-020-00007-6.

Kovács, I., Husti, I. (2018). The Role Of Digitalization In The Agricul Tural 4.0 – How To Connect The Industry 4.0 To Agriculture. *Hungarian Agricultural Engineering*, 33, 38-42.

Kuska, M. T., Heim, R.H. J., Geedicke, I., Gold, K. M., Brugger, A., Paulus, S. (2022). Digital plant pathology: a foundation and guide to modern agriculture. *Journal of Plant Diseases and Protection*, 129, 457–468.

Lima, C. F., M.; Leandro, D.A., M.E.; Valero, C., Pereira Coronel, L.C.; Gonçalves Bazzo, C.O. (2020). Automatic Detection and Monitoring of Insect Pests—A Review. *Agriculture*,10, 161. [CrossRef].

Luo, B., Sun, H., Zhang, L., Chen, F. (2024). Advances in the tea plants phenotyping using hyperspectral imaging technology. *Front. Plant Sci.*, 15, https://doi.org/10.3389/fpls.2024.1442225.

Magarey, R. D., Travis, J. W., Russo, J. M., Seem, R. C., and Magarey P. A. (2002). Decision support systems: quenching the thirst. *Plant Disease*, 86: 4–14.

Mahlein, A.K., Kuska, M.T., Behmann, J., Polder, G., and Walter, A. (2018). Hyperspectral sensors and imaging technologies in phytopathology: State of the art. *Annu. Rev. Phytopathol*., 56, 535-558.

Mahlein, A.,1 Barbedo, J.G.A., Chiang, Kuo-Szu, DelPonte, E.M., Bock,C.H. (2024). From Detection to Protection: The Role of Optical Sensors, Robots, and Artificial Intelligence in Modern Plant Disease Management. *Phytopathology*, 114, 1733-1741. https://doi.org/10.1094/PHYTO-01-24-0009-PER

Manavalan, R. (2020). Automatic identification of diseases in grains crops through computational approaches: A review. *Comput. Electron. Agric*., 178, 105802. [CrossRef].

Mihajlow, R., Ivanova, A. (2019). Drone Video Capture – A New Method In Precision Agriculture. *Annual Journal of Technical University of Varna*, 3 (2), 32-38.

Mihaylov, R., Atanasow, A., Ivanova, A., Marinov, A., Zahariev, S. (2020). Tracking The Development Of Six Wheat Varieties Using Infrared Imaging And Image Processing Algorithms. *International Conference Automatics and Informatics* (ICAI), DOI: 10.1109/ICAI50593.2020.9311317

McCown, R.L. (2002). Changing systems for supporting farmers' decisions: problems, paradigms, and prospects. *Agricultural Systems*, 74 (1), 179-220.

Ministry of Agriculture and Food, 2024. Statistics and Analyses | Ministry of Agriculture

Morgan, D., Walters, K. F. A., Oakley, J. N., and Lane, A. (2000). An Internet-based decision-support system for insect pests of rape. *EPPO Bulletin*, 30, 155–158.

Neblette, C.B. (1927) Aerial photography for study of plant diseases. *Photo Era Mag*, 58, 346.

Nikolov, D., Boevski, I., Borisov, P., Atanasova-Chopeva, M., Kostenarov, K., Petkow, E., Fidanska, B. (2022). Digitization in agriculture - competitiveness and business models. Monography. *Institute of Agricultural Economics*, ISBN 978-954-8612-40-1, p. 308

Njoroge, J. B., Ninomiya, K., Kondo, N., Toita, H. (2002). Automated fruit grading system using image processing, In SICE 2002. *Proceedings of the 41st SICE Annual Conference*, 2: 1346–1351.

Noskov, A., Bendix, J., and Friess, N. (2021). A review of insect monitoring approaches with special reference to radar techniques. *Sensors*, 21. **https://doi.org/10.3390/s21041474**

Patel, R. (2012). The Long Green Revolution. *The Journal of Peasant Studies*, 40(1), 1–63. https://doi.org/10.1080/03066150.2012.719224

Purnhagen, K. P., Clemens, S., Eriksson, D., Fresco, L. O., Tosun, J., Qaim, M., Visser, R. G. F., Weber, A. P. M., Wesseler, J. H. H., and Zilberman, D. (2021). Europe's Farm to Fork strategy and its commitment to biotechnology and organic farming: Conflicting or complementary goals? *Trends Plant Sci*., 26, 600-606.

Rydhmer, K., Bick, E., Still, L., Strand, A., Luciano, R., Helmreich, S., (2022). Automating insect monitoring using unsupervised near-infrared sensors. *Sci. Rep*., 12, 2603. https://doi.org/10.1038/s41598-022-06439-6

Rupnik, R., Kukar, M., Vračar, P., Košir, D., Pevec, D., Bosnić, Z. (2019). AgroDSS: A decision support system for agriculture and farming. *Computers and Electronics in Agriculture*, 161: 260-271.

Shtienberg, D. (2013). Will Decision-Support Systems Be Widely Used for the Management of Plant Diseases? *Annual Review of Phytopathology*, 51, 1-16;

Singh, V., Sharma, N., Singh, S. (2020). A review of imaging techniques for plant disease detection. *Artificial Intelligence in Agriculture*, 4, 229-242.

Slavova, G. (2022). Development Of Digital Agriculture In Bulgaria - Opportunities, Obstacles, Prospects. DOI: https://doi.org/10.36997/ARA2021.48, (Bg)

Skvortsov, E. (2019) How digital agriculture and big data will help to feed a growing world https://www.ey.com/en_gl/consulting/ 2021

Staford, J. V. (2000). Implementing precision agriculture in the 21st century. *Journal of Agricultural Engineering Research*, 76(3), 267–275.

Stefanova, V., Arnaudova, Zh. (2020). Ahp Analysis For Microzoning Of Vineyards By Gis. *AgroLife Scientific Journal*, 9(2). Retrieved from https://agrolifejournal.usamv.ro/index.php/agrolife/article/view/284

Stoynev, K. (2004). Ecological and technological aspects of modern agriculture. *Ed. Ecoinnovation EOOD*, (Bg).

Vasileva, T., Nedkov, R., Borisova, D., Sholev, D. (2018). MODIS satellite data for estimating actual evapotranspiration in Bulgaria (2000-2014). Proceedings Volume 10783, *Remote Sensing for Agriculture, Ecosystems, and Hydrology* XX; 107830G. DOI: https://doi.org/10.1117/12.2325771

Visakh, R. L., Anand, S., Reddy, S.B., Sah, Jha, U.C., Prasad, R., Beena, R. (2024). Precision Phenotyping in Crop Science: From Plant Traits to Gene Discovery for Climate- Smart Agriculture. *Plant Breeding*,0,1–29 **https://doi.org/10.1111/pbr.13228**

Wallhead, M., and Zhu, H. (2017). Decision Support Systems for Plant Disease and Insect Management in Commercial Nurseries in the Midwest: A Perspective Review*. J. Environ. Hort*.,35(2):84–92.

Wang, S., Peng, Q., Zhang, W. and He, X. (2022). Development and Application of an Intelligent Plant Protection Monitoring System. *Agronomy*, 12, 1046. https://doi.org/10.3390/agronomy12051046

World Commission on Environment and Development (WCED) (1987). Our Common Future. Oxford: Oxford University Press*. Our Common Future: Report of the World Commission on Environment and Development.*

Yordanov, Y. (2020), National Soil Service, Precision Farming, Digital and Smart Farming - How Are They Really Different? (Bg) http://:nationalsoils.com/

Zarco-Tejada. P.J., Camino, C., Beck, P.S.A., Calderon, R., Hornero, A,, Hernández-Clemente, R. (2018) Previsual symptoms of Xylella fastidiosa infection revealed in spectral plant-trait alterations. *Nat Plants*, 4, 432–439.

Zarco-Tejada. P.J., Poblete, T., Camino, C., Gonzalez-Dugo, V., Calderon, R., Hornero, A. (2021) Divergent abiotic spectral pathways unravel pathogen stress signals across species. *Nat. Commun*.,12: 6088. https://doi.org/10.1038/s41467-021-26335-3

Zhai, Z., Martínez, J.F., Beltran, V., Martínez, N.L.(2020). Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agric*., 170, 105256

Zhu, H., Rosetta, R., Reding, M. E., Zondag, R. H., Ranger, C. M., Canas, L., Fulcher, A., Derksen, R. C., Ozkan, H. E., and Krause, C. R. (2017). Validation of laser-guided variable-rate sprayer for managing insects in ornamental nurseries. *Transactions ASABE*, 60(2), 337-345.