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Review

Innovations in Disease Detection and Forecasting: A Digital Roadmap for Sustainable Management of Fruit and Foliar Disease

Gultakin Hasanaliyeva [1], Melissa Si Ammour [1], Thaer Yaseen [2], Vittorio Rossi [1] and Tito Caffi [1,*]

[1] DIPROVES, Sustainable Crop Protection Area, Università Cattolica del Sacro Cuore, Via E. Parmense 84, 29122 Piacenza, Italy; gultakin.hasanaliyeva@unicatt.it (G.H.); melissa.siammour@universite-paris-saclay.fr (M.S.A.); vittorio.rossi@unicatt.it (V.R.)

[2] FAO Regional Office for Near East and North Africa, Cairo P.O. Box 2223, Egypt; thaer.yaseen@fao.org

* Correspondence: tito.caffi@unicatt.it

Abstract: In a quickly growing world, there is increasing demand for a secure food supply, a reduction in the intensive use of natural resources, and the enhancement of sustainability for future long-term maintenance. In this regard, plant health, including fruit and foliar diseases, which can cause a vast amount of crop loss, potentially has a huge effect on food security. The integration of new, innovative technological tools and data management techniques into the traditional agricultural practices is a promising approach to combat future food shortages. The use of the same principles of precision agriculture to "do the right thing, at the right time, in the right place" will allow for providing detailed, real-time information that will help farmers to protect their crops and choose healthier, as well as more productive, farming methods. The presented narrative review reports on several items of innovation, including monitoring and surveillance, diagnostic, and decision-making tools, with a specific focus devoted to digital solutions that can be applied in agriculture in order to improve the quality and the speed of the decision-making process and specifically, to set up a digital collaboration that can be crucial under certain circumstances to reach sustainability goals, particularly in the Near East and North Africa (NENA) Region, where an effective and rapid solution for phytosanitary control is needed.

Keywords: sustainable agriculture; decision support systems; monitoring tools; IPM; decision making in agriculture

Citation: Hasanaliyeva, G.; Si Ammour, M.; Yaseen, T.; Rossi, V.; Caffi, T. Innovations in Disease Detection and Forecasting: A Digital Roadmap for Sustainable Management of Fruit and Foliar Disease. *Agronomy* **2022**, *12*, 1707. https://doi.org/10.3390/agronomy12071707

Academic Editor: Paul Kwan

Received: 3 June 2022
Accepted: 16 July 2022
Published: 19 July 2022

1. Introduction

According to the Food and Agriculture Organization of the United Nations (FAO) and the International Plant Protection Convention (IPPC), pests can be defined as "any species, strain or biotype of plant, animal or pathogenic agent injurious to plants or plant products" [1,2]. Pests can cause enormous crop loss worldwide. Damage can occur both in the field, from sowing to harvesting, as well as during storage. Major historical consequences of plant disease epidemics include the Irish Great Famine (1845) due to potato blight, and the Bengal famine (1943), caused by brown spot of rice [3]. The science of plant pathology addresses the cause, biology, epidemiology, subsequent losses, and management of plant diseases.

A secure food supply for future generations requires environmentally safe and sustainable production. Different types of pests and abiotic stress factors (e.g., deficiency of nutrients, drought) reduce the quantity and quality of agricultural and horticultural crops worldwide. Meanwhile, the intensive production of agricultural crops reduces soil nutrients and the maintenance of long-term environmental sustainability [4]. The main goal of modern agriculture is to reduce intensive fertilizer and pesticide use and decrease the heavy exploitation of natural resources (water, soil, energy) [5,6]. Therefore, the integration of digital innovations and technologies with traditional agricultural practices could be an option for more sustainable and secure crop/food production [7]. This approach perfectly matches the aims and spirit of the Sustainable Development Goals adopted by all United Nations Member States in 2015 [8]. For instance, precision agriculture is a collection of agricultural practices that focus on specific areas of the field at a particular moment in time. The main goal of precision agriculture can be summarized as doing "the right thing, at the right time, in the right place" [9]. This is opposed to more traditional practices, where the various crop treatments, such as irrigation and the application of fertilizers, pesticides, and herbicides, are homogenously applied to the entire field, ignoring any variability within the field, and are often carried out according to calendar-based scheduling. Precision agriculture is widely studied to target related technologies, environmental effects, economic outcomes, adoption rates, and drivers [10]. It aims to achieve real-time, robust mapping systems for crop, soil, and environmental variables to produce management decisions [11]. In addition to arable field production, precision agriculture has been successfully applied in viticulture, livestock production, and pasture and turf management. It has a vast range of uses, from tea production in Sri Lanka and Tanzania to sugar cane production in Brazil, rice cultivation in China and India, and sugar beet growth in Argentina, Australia, Europe, and the US [9,12]. Although it is difficult to define the scope of the scale of benefits, when applying precision agriculture, a review of 234 studies was presented that proves an average of 68% profitability in all cases [13]. A study conducted in Germany through the use of a simulation model (MODAM) over 11 years indicated the preventive effect of precision agriculture practices on soil erosion in terms of tillage reduction, direct seeding methods, catch crops, etc. [14]. Another study conducted in Argentina shows how site-specific information and variable rate application can benefit profitability while decreasing N application [15].

Precision agriculture tools have been in use for more than three decades now, by supporting farmers and farm managers in decision making at different spatiotemporal scales [16]. Precision tools, such as sensors and mapping fields, allow farmers to better understand their crops at a micro-scale, reducing the use of natural resources and impacts on the environment [17]. Although, in the beginning, precision agriculture was applied for the optimization of fertilizer use depending on soil variety across the agricultural field, its use has evolved into the use of automatic guidance of field vehicles and implements, autonomous machinery, product traceability, on-farm research, and software for agricultural management [9].

To our knowledge, there are a reasonable number of benefits arising from the above-mentioned practices; nevertheless, precision agriculture technologies are not extensively adopted [18–20]. According to Pierpaoli et al. [8], precision agriculture technologies are mainly adopted by educated farmers who own large farms and are interested in enhancing soil quality in the face of growing competitive pressure. The main leverages for adoption, in this case, are farm size, higher revenues to acquire a positive benefit/cost ratio, total income, land tenure, familiarity with computers, and access to information via extension services or professional service providers [10]. Non-adopters usually show low interest due to their lack of technological tools or skills, low competence to manage precision agriculture tools (or lack of financial resources to purchase them), and smaller farm sizes. Therefore, in-field demonstrations, free trials, support from experts, and simplicity of new technology should be fundamental approaches in order to avoid difficulties projected by non-adopter users (farmers) [21,22]. A virtual international diagnostic network was recently proposed [23] to facilitate the exchange of non-trade-sensitive diagnostic information and resources, enhance cooperation among diagnosticians around the world, and facilitate interaction with the global research community.

The future goals of sustainability include the enhancement of digital tools' application in many different sectors, including agriculture. Agriculture is contributing to global warming through its considerable emissions of greenhouse gases, producing more greenhouse gas (GHG) emissions than the transport sector [22]. Therefore, reducing food losses and waste can significantly reduce the impact of food production on the Earth's ecosystems; at the same time, we need to set out a plan to make food available to about 2.5 billion additional individuals between now and 2050 [24]. All modern governments should commit to tailoring their agriculture, food, and nutrition policies to reflect a sustainable approach. Governments should provide incentives for sustainable development, following the roadmap provided by the UN [8]. A positive example was provided by the EU Directive 128/2009 on the sustainable use of pesticides (SUD), which was adopted in all the European countries to "establish a framework to achieve a sustainable use of pesticides by reducing the risks and impacts of pesticide use on human health and the environment and promoting the use of integrated pest management and alternative approaches or techniques such as non-chemical alternatives to pesticides" [25]. With the recent scientific advancements, technological innovations, and legislative tools, it is now possible to achieve these strategic goals and increase sustainability in agriculture. An enlarged network based on the principles, techniques, and tools of precision agriculture at a regional, national, or even international scale could also represent a great step forward for small farms, easily providing information about what is happening in their fields and offering expert information about how to manage possible plant health risks and threats in a timely manner.

The main goal of this manuscript is to create a narrative review covering different topics related to crop protection and plant health and, in particular, monitoring and surveillance, diagnostic as well as decision-making, tools to highlight the differences between stand-alone and provoked use, and collaborative, information-based, and proactive implementation in agriculture. This approach, despite not being structured as a systematic or a meta-analytic review, consists of critical analysis of the literature published on the abovementioned topics [26]. The aim of a narrative review is, in fact, to provide a broad perspective, in this case the drafting of a digital roadmap useful in sustainable disease management, without the ambition of providing quantitative answers to specific questions [27].

The first list of articles, book chapters, and reviews was retrieved from the Scopus database using three different research strings combining #crop_protection with #decision_making, #diagnosis, and #surveillance, obtaining a list of 593, 167, and 95 articles, respectively. The selection of noted and analyzed articles was developed during the International Year of Plant Health, in collaboration with the Regional FAO office of the Near East and North Africa (NENA). In fact, this area can be considered a representative case study in which an effective and rapid solution for phytosanitary control is needed: even though the countries in this area achieved their international pledge to reduce the share of the population suffering from hunger, the overall prevalence of undernourishment has increased over the last 25 years because of conflicts and protracted crises. Thus, increasing the global awareness of new technologies available to protect plant health can trigger the development of a "digital collaboration" to help end hunger, reduce poverty, protect the environment, and boost economic development.

2. Surveillance and Monitoring Tools

The implementation and practical application of forecasting, early warning, and monitoring systems regarding pests of the main agricultural crops have been defined as among the major goals of the SUD to reduce the environmental impact and make agriculture more sustainable [25]. Growers and operators of the sector, therefore, require information and warnings that can be provided by forecast models and/or by integrated monitoring or surveillance systems (Table 1) [25]. From this point of view, the SUD pushed regional services, agricultural development services, agricultural operators, and professionals to adopt and consult new tools and technologies available in their geographical areas, to be able to act only when a certain threshold is reached, or the potential presence of pests is realized.

For some diseases, and specifically, for different insect pests, the monitoring of related attacks and population dynamics is essential for the determination of alert thresholds and intervention times. From a certain perspective, the application of epidemiological forecasting models can provide interesting results in controlling the spread and/or development of pests and diseases. Monitoring remains a key aspect for implementing and validating existing models or for calibrating epidemiological models when they are used in a new area, as well as for creating new models by understanding macro-phenomena and the dynamics of harmful organisms [16]. Field scouting is necessary to provide initial inputs detected in the field for triggering some models [28], to keep the actual phytosanitary threats for a crop under control, and to carry out a timely verification of the efficacy obtained by several plant protection products, or the possible occurrence of pest resistance towards specific active substances.

Moreover, appropriate monitoring systems are also important, both to detect inoculum outbreaks and to follow their evolution, particularly for the diseases that cannot be controlled by direct methods, but for which the identification and localization of the affected plants are fundamental for limiting their spread (e.g., Esca disease in grapevines, as well as other trunk diseases, and root rots in different crops). The early detection of new outbreaks and phytosanitary emergencies related to newly introduced alien pests in a specific area (e.g., *Xylella fastidiosa* in olive trees in Europe, *Flavescence doree* in grapevines in northern Italy, or *Ralstonia solanacearum* in tomatoes in the Emilia-Romagna region of Italy) are the key scope of monitoring activities to apply the appropriate quarantine phytosanitary measures and/or evaluate, in real-time, the phytosanitary situation of a region or an area in a timely manner.

Finally, scouting activities are necessary to detect and monitor any abiotic stress related to soil modification (e.g., soil erosion or organic matter reduction), to be able to properly react or characterize the concerned area (e.g., nutrient deficiency, salinity, abnormal pH, pollution, etc.), and to detect damages from abiotic stresses covered by insurance policies to facilitate the quantification of compensation.

Several sensing technologies are used in precision agriculture, helping to monitor yield, the rate of fertilizer use, weed occurrence, insect abundancy, soil properties, water requirements, crop harvest readiness, and many other factors [17]. The geographic information system is one of the advantages of modern technology, benefitting precision agriculture in many ways. It allows for analyzing and processing a large amount of data in a short time by providing uniform measurements for large areas in a digital form [29]. This technology makes it possible to use only the optimal amount of fertilizer, which prevents wasting money and polluting the environment [30]. For instance, crop yield monitoring is very important for farmers to consider future expectations. In this case, data (i.e., the amount and rate of harvest) obtained from site sensors are combined with a global positioning system (GPS) for the location of each data point, providing information to produce crop maps in a geographic information system (GIS). This map can later help to manage a site-specific program in future years [29]. GIS is an essential technology for decision-making systems [30], generating various types of spatial and description data. According to Tayari et al. [29], remote sensing (RS) techniques, such as satellite images, are a powerful tool, providing 95% accuracy in the estimation of the area under cultivation within a month. Thus, tools such as GIS, GPS, and RS could be a possible option for determining variability and other factors on a farm [6,7,29]. Examples of agricultural sensors include location sensors such as GPS satellites for the determination of latitude, longitude and altitude; optical sensors for measuring soil properties (i.e., clay, organic matter, and moisture) by means of light reflectance; electrochemical sensors for soil pH and nutrients; mechanical sensors to measure soil compaction and force used by roots for water intake; and weather stations to measure air and soil temperature at various depths, rainfall, chlorophyll, wind speed and direction, dew point temperature, humidity, solar radiation, and atmospheric pressure [17].

In recent years, sensor technologies have also been applied to insect monitoring. For instance, image-based e-traps that require further interpretation by human experts are already on the market [31–33]. However, more research is ongoing to develop low-cost and labor-effective automatic insect monitoring tools. Potamitis et al. [34] studied an innovative approach based on a bimodal wingbeat recorder and acrylic Frensel optic sensor, which looks at wingbeat from different perspectives and allows one to set up a lower budget and more specific wingbeat analysis, enhancing the quality of monitoring services [34].

Wireless sensor network (WSN) technologies have become an essential part of precision agriculture because of recent advances in wireless communications systems. The use of WSNs allows farmers to increase efficiency, productivity, and profitability while reducing the negative effects of agricultural production on wildlife and the environment [35]. Real-time data obtained by WSNs can contribute to lessening potential production risks, caused by the environment or humans [36], and energy consumption, and help farmers to modify production strategies at any time, without using traditional manual or machinery-based methods [36]. The transition towards sustainable agriculture requires cleaner crop production techniques based on WSNs. Wireless sensor technologies have mainly been deployed in greenhouses or gardens, rather than in actual fields. The data obtained from sensor nodes are wirelessly transmitted to a central base of data collection for a decision on relevant management measures like drip irrigation [36]. However, a large-scale WSN experiment was also conducted in the Netherlands to obtain better crop production alongside the optimal use of resources [37].

Drones in agriculture are promising tools to easily overcome several challenges, such as soil and field analysis, that farmers face during crop production and protection, allowing farmers to be aware of farm conditions from the beginning of the cropping cycle (i.e., generated data can be used to evaluate irrigation and nitrogen rate for crop growth). They can be useful to monitor the vegetative status of the crop through thermal sensors and allow for the adjustment of the irrigation rate, as well as to calculate the vegetation index and the crop health status. Unmanned aerial vehicles (UAV) are another tool of precision agriculture for monitoring purposes. Similar to drones, UAVs are aircraft with no onboard crew or passengers, most commonly used for the surveillance of crop Conditions, soil properties, water content and weed distribution [38]. Differing from drones, which are remotely piloted by humans, UAVs have "automatic intelligence" that controls both flying activities and loading imaginary data, along with other information [38]. UAVs with relevant sensors can deliver easy access to the field plots and difficult landscapes, while also enabling crop growth monitoring at lower operational costs [9,39,40]. Another advantage of UAV technology is crop yield monitoring: multispectral imaging helps growers to predict the yield and consequently, the market value, of their crop [38]. UAV-based sensing helps to monitor plant growth parameters, such as emergence or flowering, vigor, and leaf area index [41,42], and can use a wide range of technologies such as light detection and ranging (LIDAR), visible to near-infrared, and/or thermal imaging [41]. Installed infrared, NVDI, or multispectral sensors on drones allows farmers to track crop health and take protective actions beforehand [43]. Although UAV remote sensing technologies have some limitations, such as reduced flight time, meaning that they require more flights for covering larger areas and to meet strict aviation regulations, in addition to the lack of a standardized methodology for processing a high volume of UAV images, they can still benefit precision agriculture in many ways [38].

The Internet of Things (IoT) is another promising technology in terms of monitoring and control in a large-scale farming systems [7,44]. It allows for better productivity and sustainability in many ways, such as, for instance, achieving better sensing and monitoring of production and obtaining a better understanding of the specific farming conditions (i.e., weather, environmental conditions, animal welfare; pest, weed, and diseases management) [44]. The more sophisticated and remote control of farm, processing, and logistics operations can be enhanced by actuators and robots (e.g., precise application of pesticides and fertilizers, robots for automatic weeding); these can also improve food quality with the control of environmental conditions during transportation [44]. Thus, the IoT is offering novel opportunities beyond farming, benefitting food manufacturing as well [45].

Monitoring tools are more effective when used in combination with networking arrangements based on institutional agreements to monitor locusts, fall armyworm, and wheat rust diseases. The desert locust is a well-known invasive pest in the region between

West Africa and India. The FAO Desert Locust Information Service (DLIS) operates an early warning system that collects locust-related data and produces monthly situation summaries and forecasts for each country [46]. The recently developed eLocust3 tool records and transmits real-time data to the national locust centers. These data are used to assess the current situation, forecast infestation, and provide preventive control strategies for affected countries [46].

The Lepidoptera *Spodoptera frugiperda*, commonly known as fall armyworm (FAW), is a major pest that affects farmers in many countries of the NENA region. The FAO has developed the new FAW Monitoring and Early Warning System (FAMEWS) for Africa, allowing users, through the mobile app, to collect scouting, trapping, farming, and crop data [47]. Such disclosed data can be mapped in a GIS and thus, provide insight into the population behavior of FAW and guide growers regarding the best management practices [48].

Wheat rust diseases are a major threat in almost all wheat-growing countries. The FAO cooperates with different countries to develop effective surveillance and early warning systems against rust diseases [49], and rusttracker.cimmyt.org is the web portal for global cereal rust surveillance and monitoring information. It provides up-to-date information on different features of wheat rust, such as incidence and severity, resistant cultivars, and the availability of interactive, database, and visualization tools [50].

Table 1. Tools adopted for surveillance and monitoring, according to the traditional approach, and possible improvements provided by a more advanced, digital-based approach.

Traditional Approach	Advanced Approach	Improvements
Weather stations Soil sensors Soil and plant analysis	Wireless Sensor Network (WSN) Advanced sensors (IoTs)	Wider range of information with increased efficiency [35,36,44]
Field monitoring	Proximal and remote sensing: Geolocalization (GPS, GIS) Drones, UAVs, Satellites Monitoring platform	Increased data precision, geo-positioning [6,7,29,30] Large-scale monitoring [41–43] Reduced time and cost of the monitoring process [46–50]
Pheromones traps	Image-based traps	Real-time data availability [31–34,36]

3. Diagnostic Tools

Disease management practices essentially rely on preventing the occurrence of disease and targeting critical stages of the pathogen in the disease cycle. Correct disease diagnosis is always essential to identify the right causal agent (Table 2). Therefore, plant health treatments are usually applied based on correct disease forecasting models [51]. The main diagnostic method of a plant disease remains the confirmation of Koch's postulates, starting from a symptomatic plant or organ to verify the hypothesis that the isolated pathogen is the actual cause of the disease [52]. Based on artificial intelligence advances, analyzing and identifying images of the pest damage could greatly help farmers in diagnosing the disease or the insect pest in seconds, even without a connection to the Internet. Nuru is one of these tools helping many farmers in Africa to diagnose fall armyworm (FAW) in their fields [48]. Specific image analysis software (e.g., Assess 2.0, Lamari APS Press) can also be used on pictures of affected organs or canopies, and it represents another useful tool for estimating disease severity on different vegetative organs by, for example, quantifying the size of chlorotic and/or sporulating lesions on grapevine leaves affected by downy mildew [53]. The use of machine learning approaches for the diagnosis of plant pests is progressing rapidly.

An integrated disease control program aims at (i) eradicating or reducing the initial inoculum, (ii) reducing the effectiveness of the initial inoculum, (iii) increasing the host resistance, (iv) delaying the disease onset, and (v) slowing down the secondary cycles [52]. It is crucial to accurately detect and identify pathogens to initiate preventive disease control measures. An essential factor in disease management is the early detection of pathogens, particularly in seeds, mother plants, and propagative plant material, but also in the early stages of the infection to avoid the introduction and further dispersal of the inoculum [54]. On-site nucleic acid-based methods that can be performed with minimal equipment, rapidly, and at low cost, are receiving growing interest in plant pathology. Indeed, continuous advances in DNA-based detection methods have provided fast, sensitive, and reliable detection and quantification of fungal pathogens, when compared to culture-based identification methods [55]. Most of these techniques rely on polymerase chain reaction (PCR) and real-time PCR (RT-PCR) assays, which have been extensively applied to plant pathology from the soil, water, air, and plant material [56–62]. Moreover, PCR-based techniques provide highly specific assays that can discriminate between species isolates and genotypes [63,64].

Scientific development has been achieved by moving real-time PCR technology from the laboratory to the field using a portable thermocycler [59,65,66]. Despite some successful applications, these technologies have not been widely adopted, as the portable thermocyclers are expensive, and the assays require laborious modifications to adapt DNA extraction protocols to the field conditions [67,68]. Recently, the insulated isothermal PCR (iiPCR) POKIT system was introduced for sensitive and specific on-site detection of nucleic acid [69], and it is a relatively simple and inexpensive device when compared to thermocyclers [70].

Isothermal amplification detection methods have been developed to overcome the challenges of the use of PCR thermocyclers for possible on-site testing. As the name suggests, the isothermal amplification of DNA (or RNA) occurs at a constant temperature, which confers to some of these methods the potential for use in the field by means of portable instruments [69]. Many reviews have fully described these methods for isothermal amplification [71–74].

The loop-mediated isothermal amplification (LAMP) [75] method has attracted much attention, as it provides a rapid, accurate, and cost-effective diagnosis of diseases. Numerous reports have been recorded to evaluate its efficiency in recognizing bacterial, viral, fungal, and parasitic diseases worldwide [76–80]. In the initial phase of development, LAMP was applied to many kinds of pathogens causing food-borne diseases, and LAMP kits for detecting salmonella, legionella, listeria, verotoxin-producing *Escherichia coli*, and campylobacter have been commercialized [81]. Recently, a growing interest in this method has been also observed in the detection of plant pathogenic agents, especially with the possibility of in-field application through portable devices [82–87]. For instance, the LAMP method, combined with lateral flow strips or portable fluorometers, has been developed to enable the field detection of plant pathogens such as *Erwinia amylovora*, *Candidatus* Liberibacter asiaticus, *Erysiphe necator*, and *Phytophthora infestans* [83,85,88–90]. More recently, handheld instruments have been made available for real-time isothermal detection. Most of these instruments consist of a simple heating block, with a testing capacity of eight standard 0.2 mL tubes, and usually include dual-channel fluorescence measurement to allow for the use of internal controls and multiplexed assays. Some of them also provide positional information through GPS, in addition to wireless connectivity via Bluetooth and Wi-Fi.

Piepenburg et al. [91] first introduced recombinase polymerase amplification (RPA) as another isothermal technique for diagnostics. The RPA method has been extensively used in clinical trials [92–97]; however, many RPA assays have been developed to detect plant pathogens. Reverse transcriptase RPA (RT-RPA), for instance, has been applied for the detection of important plant viruses, such as plum pox virus, little cherry virus, and tomato yellow leaf curl virus, and has proven to be more cost-effective and sensitive than RT-PCR and ELISA [89,98,99]. Recently, Miles et al. [100] used RPA approaches to develop a genus-specific assay for the detection of *Phytophthora* spp., and other assays for *P. ramorum* and *P. kernoviae* species detection from crude plant extracts.

Surely, phytopathology can benefit from the use of affordable and robust on-site assays, as plantations can be distant from diagnostic laboratories; in particular, there can be a long interval of time between sampling and diagnosis, and in some cases, it would be highly recommended to perform testing at the sampling site (e.g., quarantine plant pathogens). On-site molecular testing requires not only a portable platform and suitable assay, but also a simple and robust alternative DNA extraction method that can be performed in the field. The preparation of a sample has traditionally been difficult and time-consuming. It is widely known that plant tissue samples require DNA extraction methods that are able to efficiently wash away any chemical compound and that can inhibit the DNA amplification reaction [101]. However, isothermal assays were shown to efficiently detect plant pathogenic DNA from crude extract samples [68,83,98,100,102] using simple and short sample preparation methods.

Table 2. Tools adopted for fruit and foliar disease diagnosis, according to the traditional approach, and possible improvements provided by a more advanced, digital-based approach.

Traditional Approach	Advanced Approach	Improvements
Traditional diagnostic methods based on symptoms or functional changes or recovery factors	Image analysis software	More precise disease quantification [53]
	Artificial intelligence, machine, learning,	Shortened diagnostic time [48]
	ELISA PCR, RT-PCR LAMP RT-RPA	More precise diagnosis [55,63,64] In-field analysis [82–87] Simple and short sample preparation methods [98,100,102]

4. Decision Making

Adequate pest monitoring, using suitable methods and tools, including field observations, the use of insect/spore traps, and forecasting systems, is essential for guiding decision making in IPM. To support decision making (at strategic, tactical, and operational levels) in crop protection, a large number of tools predicting the dynamics of harmful organisms and the guidance of their management have been developed, including population dynamics and epidemiological models, risk algorithms, intervention thresholds, decision rules, and decision support systems (Table 3). In this review, all these tools are collectively called decision tools (DTs). DTs help decision makers to solve complex problems, while reducing the time and the resources allocated for analyzing the available information and selecting the best solution [103].

Decision support systems (DSSs) represent the holistic vision of crop cultivation problems: they take into account and provide decision support for all of the key elements of the production chain, from strategic choices to tactical operations. These DSSs use sophisticated technologies and methods for analyzing data to produce simple and easy-to-understand decision support information in order to convert complex decision processes into simple decision support frameworks that can be easily and clearly used by farmers. A properly designed DSS is an interactive software-based system that helps decision makers to obtain useful information from raw data, documents, personal knowledge, and/or models in order to identify and solve problems, make informed decisions, and apply correct actions. DSSs can be as simple as a tool for processing data or as complex as an expert computerized system. DSSs collect, organize, and integrate all types of information required for producing crops; DSSs then analyze and interpret the information, and finally use the analysis to recommend the most appropriate action or action choices [52]. Expert knowledge, mathematical models, and timely data are key elements of DSSs, and are used to assist producers both with daily operational and long-range strategic decisions [16,104]. Computer-based DSSs have the potential to be important tools in the decision-making process for farmers and their advisers [105]. DSSs can potentially include all the requirements for the practical implementation of IPM.

Different authors [104,106] analyzed and mentioned the limitations of previously developed DSSs, which have been recognized as an obstacle to their adoption and sustained use in agriculture. A new generation of DSS recently faced the complexity of decision making in agriculture under the IPM regime, but at the same time, showed how it is possible to overcome the limitations of traditional DSSs [107]. The implementation of these new generation DSSs as web applications should increase their accessibility, but also speed up and facilitate their maintenance and updating with the newest results and outcomes coming from researchers. New DSSs do not conflict with information derived by regional/local warning services, but rather enlarge their efficacy, coupling information from both the territorial scale and the crop scale. In the context of the above-mentioned SUD, site-specific data, scouting reports, and recommendations from the DSSs will serve as acceptable criteria for justifying (to regulatory authorities, wholesalers, or processors) the application of chemicals. The innovative approach in elaborating new generation DSSs [16,104,107] can be summarized as (i) preserving the natural resources of the cropped field for future crop production; (ii) improving the economic viability of the crop through better management of the resources and reducing certain inputs (e.g., chemicals, water, etc.); (iii) demonstrating good environmental performance to customers, neighbors, and the general community; (iv) meeting industry, community, and government expectations about environmental management; and (v) maintaining or providing access to certain markets, especially those with high environmental standards. These DSSs are characterized by two main parts: (i) an integrated system for the real-time monitoring of the field crop components (air, soil, plants, pests, and diseases); and (ii) a web-based tool that analyses these data by using advanced modelling techniques and then providing up-to-date information for managing the field crop in the form of alerts and decision supports.

The application of such a type of DSS has already proved effective for the timely control of pests. For instance, the DSS for sustainable vineyard management [107] was tested in 21 organic farms in Italy (which ranged from 1 to 180 hectares) and allowed, over two seasons, the same level of grape protection obtained with the usual farm practice, with an average saving in the total amount of copper applied of 37% because of both reduced doses and fewer applications. This saving was equal to about EUR 195/ha/year for the growers. The same DSS was then applied on a large scale across Italy, confirming the positive results [107], and today, it is adopted by 400 public/private advisers for about 16,000 hectares of Italian vineyards.

Another example of innovative DSS was developed for durum wheat, and it allowed the users to obtain the same grain yield and quality as the conventional approach, in the 2012/13 season, while reducing the cultivation costs by 8.5%, the carbon footprint by 11%, and in the use of nitrogen fertilizer by 16%, along with an increase in the agronomic nitrogen use efficiency (NUE) of 12.5%, on average, compared to the farmers' usual cultivation methods [108]. In the 2013/14 season, the use of the DSS was extended on a large scale, and it allowed the users to harvest 86,500 tons of durum wheat over 17,500 hectares in Italy, with a carbon footprint of 0.48 TCO_2 eq/ha and an agronomic NUE of 35.4 kg of grain/kg of fertilizer [108]. The number of growers using the innovative DSS for sustainable wheat production has increased, and in the 2018/2019 season, more than 70,000 hectares were cropped using to the information provided by the DSS.

The approach used for the elaboration of these innovative decision tools has also been extended to different crops, such as tomato, olive, sunflower, and leguminous crops, with very promising results. The application of this type of decision tool can lead to an improved crop management strategy, based on IPM and sustainability principles.

Table 3. Tools adopted for decision making in crop protection, according to the traditional approach, and possible improvements provided by a more advanced, digital-based approach.

Traditional Approach	Advanced Approach	Improvements
Experience Consultants	Decision Support system (DSS)	Holistic approach [52]
Thresholds Simple rules or empirical models	Mechanistic, integrated models	Expert knowledge, advanced models [16,104]
Good practices, guidelines, protocols	Informed decisions	Sustainability plays a part in the decision-making process [108]

5. Conclusions

Although precision agriculture is not exclusively a new idea, the main thread of this review was about its spirit and goals, with a particular emphasis on increasing awareness about the accessibility to innovative tools for all farmers. The main purpose of describing different monitoring and diagnostic tools and early warning and decision support systems in this review was to give insight into the possibility of using precision agriculture, not only at the field scale, but also at the regional scale to reach the goal of sustainability in agriculture. In the main topic, we also discussed problems of non-acceptance of technological solutions due to the lower budget of farmers. Using innovative applications at a regional scale will lower the cost and provide a more precise forecast for robust decision making.

Remote sensing allows users to identify stressed plants, as well as soil characteristics of large areas, and also, by calculating different vegetation indexes, to obtain information on the crops' vigor for estimating crop yield. Other diagnostic tools, such as the molecular devices discussed, are crucial to accurately detect and identify pathogens to initiate preventive disease control measures. These can be used on a large scale by trained personnel and can cover a wide area to provide precise, timely, and accurate information about the presence and development of disease epidemics. Such information could be relevant to improve the precision of the entire platform and the quality of data provided.

There is, for instance, great variability in plant disease epidemics across areas and years, and such variability is closely related to the variability in weather conditions. Moreover, severe epidemics can occur in areas where the disease has not been traditionally considered a key problem. The combination of site-specific weather data, monitoring reports, and advice from a DSS enables growers to protect, for instance, their vineyards against downy mildew by modulating the frequency and timing of fungicide applications based on disease risk [108].

By providing real-time, holistic, and detailed information on the many aspects of crop status, the new-generation DSSs have been proved to be able to help farm managers to make informed decisions. In particular, they enable managers to rationalize the use of both natural resources, such as water, and technical inputs, such as plant protection products, and thereby implement a cropping system that is consistent with the principles of sustainable agriculture, including IPM, as acknowledged by the SUD in Europe. These new DDSs also enable managers to keep track of the rationale behind each management action undertaken during the cropping season. The innovative DSSs were designed to overcome the "implementation problem" previously encountered by most crop management DSSs. The key characteristics that define the new-generation DSSs is that they were purposely developed to avoid both technical limitations and a low rate of acceptance by users.

As shown in Figure 1, a digital roadmap can be defined, starting from traditional farming, where tools of the three areas (monitoring, diagnostic, and decision making) work separately, and management actions are performed individually by each farmer, on an intuitive and provoked basis. A more agile thinking is provided by the increased awareness of digital solutions that can be applied and organized together (Figure 1). Digital collaboration could be reached using a large collaborative environment between all the involved stakeholders (i.e., farmers, institutions, plant protection organizations, etc.) in order to achieve a large-scale application of the proposed tools, stimulate a proactive contribution, and to allow farmers to apply real-time, informed decisions for disease management (Figure 1). Digital collaboration can be developed in many ways, without a rigid scheme, by instead putting together different tools from different areas (monitoring, diagnostic, and decision making) so as to establish connections, interactions, and a general improvement in the speed and quality of disease management.

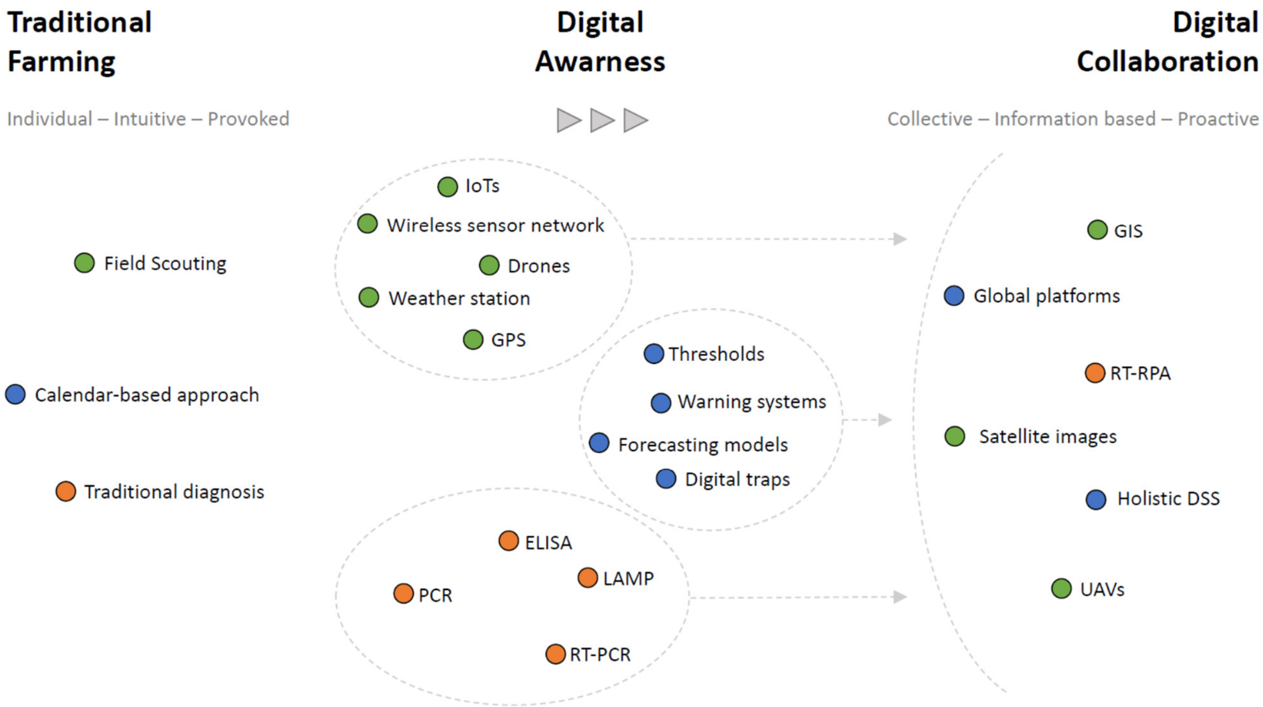

Figure 1. Digital roadmap leading to a digital collaboration era: the awareness of different digital tools available (monitoring tools—green, diagnostic tools—orange, and decision tools—blue) initiates the change from traditional farming (where the three areas are separated) to a more agile thinking (where different tools can be used, but the three areas are still separated) and finally, to a more collaborative architecture, where different tools of different areas can work together, enhancing each other.

The actual availability of innovative tools and data management techniques, also leading to big data management and analysis requirements, allows us to think about an integrated system of digital collaboration that provides phytosanitary monitoring for one (or more) crops in a specific area, which is effective, rapid, objective, and repeatable in varied environmental contexts, and therefore suitable to provide appropriate support to the various phytosanitary control needs in a region or an area. This digital collaboration environment could be integrated into modern decision support system information, protocols, and guidance to allow trained personnel to carry out surveys and data collection, through information, alerts, and guidelines (photographic or video supported) provided by the system. This supports the user in making decisions, increasing operational efficiency and reducing the possibility of making mistakes. It also makes it possible to share information or collected data with team members or organizations through the web platform in real-time. The aforementioned monitoring can be combined with the automation of the process, by means of the use of Internet of Things (IoT)-based technologies, to make the activity more precise, with a reduction in errors and implementation times, as well as costs. This approach could lead to a complementary monitoring system and enhancement of the forecast models, an aspect that will allow researchers to optimize and increase the information and alerts provided to the operator, guaranteeing a clearer and more thorough picture of the phytosanitary and physiological state of the plant. The new generation of DSSs are now ready to serve as a platform able to (i) receive input, information, and data from many different sources and tools, and (ii) store them in a repository where appropriate models can analyze them in the most appropriate way (including big-data analysis), (iii) define decision supports, and (iv) provide information to the decision makers (i.e., growers, technicians, consultants, and policymakers) in a timely, clear, and easy to understand form. This can represent a step forward in the practical application of the Sustainable Development Goals adopted by the UN in 2015 [8]. Innovative solutions described in this review are linked to at least eight different SDGs. The increased efficiency of warning system networks due to the integration of enhanced technologies will lead to a timelier application of pest control strategies, with a consequent reduction in food losses and increased food security (SDG 2), leading to a reduction in poverty (SDG 1). The enhanced quality of crop protection will engender a rationalization of, and thus a reduction in, the use of plant protection products, leading to reduced contamination of soil and water and thus, to the enhancement of clean water availability (SDG 6), as well as the protection of life below water (SDG 14) and life on land (SDG 15). Improved crop management will lead to improved food safety, and thus to improved health and well-being (SDG 3). A large-scale application of the presented solutions will provide improved learning opportunities (SDG 4) by making innovative tools more accessible to a large audience (e.g., students, farmers), while at the same time, ensuring more decent work and economic growth by providing information and knowledge (SDG 8).

The digital collaboration era will have to be tested in practice, but all the necessary technologies and knowledge are currently available and, as shown in this paper, they are ready to be coupled together and put into use in the field.

Author Contributions: Conceptualization, T.C., V.R. and T.Y.; methodology, G.H. and T.C.; writing—original draft preparation, G.H. and M.S.A.; writing—review and editing, T.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Food and Agriculture Organization of the United Nations, Near East and North Africa Regional Office.

Conflicts of Interest: The authors declare no conflict of interest.

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