Chapter 5
Pest and Disease Management

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Abstract This chapter describes the current sensing and actuation technologies for pests and plant diseases in orchards and vineyards. The technologies for pests include machine vision and imaging, trapping, data mining, nuclear magnetic resonance (NMR), DNA analysis, landscape and soil management, vibrational signals, precision spraying, and bird control. Some new technologies for pests were developed, such as predicting future infestation using artificial intelligence and pest identification using smartphone apps; however, more efforts will still be needed. The technologies utilized in plant disease detection and management include computer vision, thermography, spectroscopy, chlorophyll fluorescence, multi- and hyperspectral imaging, plant volatile organic compounds, biosensors, sensing platforms and robots, and artificial intelligence. Overall, new, reliable, easy-to-use, and objective methods will still be needed, along with continued support and interest from growers and industries.

5.1 Orchard and Vineyard Management for Pests and Diseases

Modern and sustainable agriculture requires objective and continuous monitoring of the crop. New technologies, sensors, artificial intelligence, and automation will play a more significant role in the agriculture of the future. Today, there is a wide range of new technologies whose use in monitoring crops has provided us with objective, robust, and reliable results. Subsequently, after an objective and reliable diagnosis

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of the vineyards and tree fruit orchards, we need to take action to optimize the management of pests and diseases. Efficient management of agricultural diseases and pests is crucial for eventually increasing crop yield and profit.

Agricultural pests are defined as "organisms that diminish the value of resources in which man is interested. They interfere with the production and utilization of crops and livestock used for food and fiber" (USDA ERS, 1999). They include "all noxious and damaging organisms: insects, mites, nematodes, plant pathogens, weeds, and vertebrates." This chapter is focused on insects, mites, nematodes, and vertebrates.

Common insect pests in orchards are apple maggot, brown marmorated stink bug, codling moth, leafrollers, spider mites, spotted wing drosophila, and woolly apple aphid (Beers et al., 1993). The major arthropod pests in vineyards are phytophagous mites, phylloxera, leafhoppers, mealybugs, and grape berry moths (Bostanian et al., 2012). For citrus production, common insects are Asian citrus psyllid, citrus leaf miner, citrus root weevils, citrus rust mites, spider mites, Caribbean fruit fly, and thrips (Diepenbrock et al., 2019a, b; Duncan & Mannion, 2019; Qureshi et al., 2019).

Most insect pests are controlled by cultural, biological, physical, semiochemical, and chemical controls (Bostanian et al., 2012). They emphasized that "the main challenge for integrated pest management remains the development and coordination of all information and technologies into an optimally relevant package to growers in a given area." Some new technologies were reported for site-specific viticulture (Tisseyre et al., 2007). The technologies included georeferencing information, equipment, and people and yield monitoring, in-vineyard quality monitoring, canopy and vigor monitoring, soil monitoring, water stress monitoring, and variable rate technology. They provided some example management practices for spatial and temporal variabilities. For non-pesticide management, Wilson and Daane (2017) reviewed ecological approaches for pest management in California vineyards. The methods included mating interruption, ant control for mealybugs, habitat management, natural enemy augmentation, animal integration, and biodynamic preparations. They emphasized that these practices should be "reliable and affordable" to growers for wide adoption.

Fungi, bacteria, mycoplasmas, and viruses can cause important diseases in crops. Infected plants usually show different visual and typical symptoms in different organs such as stems, leaves, and fruits; however, some plant infections can be symptomless, mainly in the early infection stages of the infection (Fig. 5.1).

Diseases can negatively affect the yield and quality of the fruit trees and can even induce the death of the plant. Crop diseases cause significant economic losses in agricultural production over the world. The environmental and economic impacts of crop protection are significant (Pimentel et al., 2005). A major impact is caused when the plant develops when the infection occurs. Plant pathogen detection is important as the first step in crop protection in agriculture. An early pathogen detection system can decrease such losses caused by plant diseases and reduce the spread of diseases (Mahlein, 2016; Mahlein et al., 2018, 2019; Thomas et al., 2018).

Fig. 5.1 Commercial vineyard infected by grapevine trunk diseases (GTD). Visual symptoms in leaves, shoots, and clusters are shown. Asymptomatic leaves were observed. (Photo: Javier Tardaguila)

This chapter presents principles, methods, and hardware and software technologies to detect, classify, and quantify pests and diseases. It also discusses state-of-the-art and emerging actuation technologies for targeted control of pests and diseases using ground and aerial platforms.

5.2 Sensing and Actuation Technologies for Pests

5.2.1 State-of-the-Art Sensing and Actuation Technologies for Pests

Pests are one of the main problems in crop production. Efficient and effective pest management is crucial for increasing yield and profit. Many different technologies have been used for pest infestation and crop damage to achieve this goal.

5.2.1.1 Machine Vision and Imaging Technologies

One of the most common methods for pest detection is machine vision, including multispectral and hyperspectral imaging. Image-based insect detection methods were developed to identify eight insect species. A correct classification rate of 87% was reported (Wen & Guyer, 2012), using various features such as geometry, contour, texture, and color. Another study (Hassan et al., 2014) also utilized color and shape features and a support vector machine (SVM) classifier to develop an automatic insect classification method for grasshoppers and butterflies as examples. They reported 92% detection accuracy. Machine vision algorithms could be used for autonomous selective pesticide spraying in vineyards (Berenstein et al., 2010), which reported a 30% reduction of applied pesticide agents.

Some study was conducted to identify spectral characteristics of insect pest infestation. Using reflectance measurement of infested leaves, Blanchfield et al. (2006) investigated an indirect method for detecting phylloxera infestation through leaf pigment composition. They reported a reduction of leaf chlorophyll and an increase in photoprotective pigment concentrations due to phylloxera infestation. Spectral measurement was also used for detecting damages by nematodes, even though the study was conducted for cotton (Lawrence et al., 2007) or sugar beet (Hillnhütter et al., 2011).

For machine vision applications, multispectral and hyperspectral imaging is commonly used. One such study was conducted by Benheim et al. (2012). They implemented multispectral and hyperspectral imaging to detect phylloxera infestation in vineyards. They reported that these imaging methods had some potential. However, they might not be able to detect the infestation since many other factors were showing similar spectral signatures, such as water stress or nitrogen deficiency. They pointed out that soil temperature, moisture content, salinity, and apparent electrical conductivity were highly correlated with the establishment and distribution of phylloxera.

UAV is also commonly used for orchard and vineyard pest management. Vanegas et al. (2018) utilized various cameras installed on a UAV to detect different levels of grape phylloxera infestation. Airborne color, multispectral, and hyperspectral images were acquired from two phylloxera-infested vineyards in Victoria, Australia. Color images and various vegetation indices were used to determine infestation levels.

Even though for other crops such as strawberries or soybean, a color image processing algorithm was implemented to detect thrips (Thysanoptera) for greenhouse strawberries (Ebrahimi et al., 2017). Combined with a support vector machine (SVM) classifier, they could correctly detect thrips with a mean detection error of 2.3% using 20 testing images. Hyperspectral transmittance images were used to detect insect-damaged vegetable soybean (Huang et al., 2013). These methods could be applied to crops in orchards and vineyards.

Electrical conductivity (EC) was used along with imaging (Bruce et al., 2009). Early detection of grapevine phylloxera was investigated using traps, soil samples, electromagnetic surveys, aerial multispectral images, and a reflectance sensor (GreenSeeker). They found that soil EC and chemical analysis indicated a potential for early detection and reported more infestation in higher soil EC areas and high magnesium contents. They described that remote sensing techniques should be able to distinguish symptoms from other stress factors, contrary to Benheim et al. (2012).

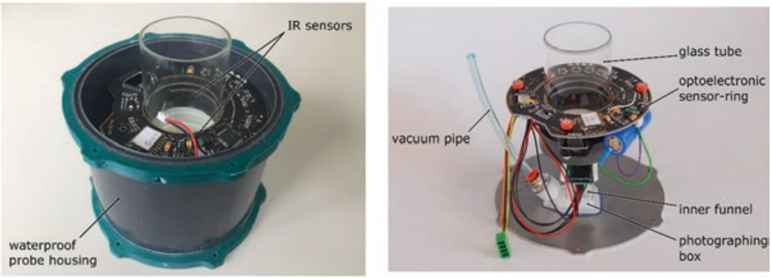

Fig. 5.2 Camera-supported trapping probe for detecting soil microarthropods with protecting tube (left) and without it (right). (Adapted from Florian et al. 2020)

Multispectral imaging also was used for nematode detection. Even for another crop (soybean), Kulkarni et al. (2008) utilized aerial four-band multispectral imaging to identify nematode population density. There was a potential for remote sensing and some difficulties due to the complicated relationship between soil nematode population and crop damage.

5.2.1.2 Trapping

Trapping is another method to detect insect pests. Hillier and Lefebvre (2012) used pheromone trapping to detect insect pests in vineyards. Renkema et al. (2014) developed a plastic jar trap for *Drosophila suzukii* and compared it with commercial traps for trapping performance. They reported some results related to trapping entry size, colors, the existence of holes, attractant volumes, headspace volume, replacement frequency, etc. More recently, Florian et al. (2020) developed a trap with an optoelectronic ring and camera for detecting soil microarthropods such as springtails (Collembola), mites (Acari), coleopterans (Coleoptera), dipteran larvae (Diptera), isopods (Isopoda), and diplopods (Diplopoda). The proposed trapping probe is shown in Fig. 5.2. Their success rate was 60–70%.

5.2.1.3 Data Mining

Tripathy et al. (2011) implemented a wireless sensor network and data mining techniques to identify relationships between pest insect (thrips) infestation and weather conditions. Using the naïve Bayes algorithm and rapid association rule mining, they identified a correlation between weather data and pest infestation and developed a multivariate regression model which can predict insect establishment and degree of infestation.

5.2.1.4 Nuclear Magnetic Resonance (NMR)

Tucker et al. (2007) used nuclear magnetic resonance (NMR) spectroscopy to detect phylloxera in grapevine leaves. Infested leaves showed metabolic changes, and their extracts, such as unsaturated fatty acids, exhibited infestation markers, even though very similar to nitrogen stress.

5.2.1.5 DNA Analysis

DNA analysis was also used. Bruce et al. (2011) integrated phylloxera-specific DNA analysis from grid soil samples with their previous study. They reported that soil-based DNA assays have the potential to detect phylloxera; however, more evaluation would be needed.

5.2.1.6 Landscape Elements and Soil Management

Landscape elements were used for insect pest management. Judt et al. (2019) investigated the effect of landscape elements and inter-row management on the arthropod populations using 15 commercial vineyards in Andalusia, Spain. The landscape elements included semi-natural vegetation, olive orchards, vineyards, and other agricultural areas. The inter-row management included vegetation cover and bare soil. The number of arthropods decreased when there were other surrounding vineyards. Also, they reported that semi-natural and olive orchards didn't affect the arthropods' population but found more arthropods from inter-row vegetation and more spiders from bare soil. These findings suggested integration of local landscape structure and inter-row management should be considered for more effective pest management.

Soil management affects insect pest infestation. Sáenz-Romo et al. (2019) studied the effects of soil management techniques (tillage, spontaneous cover, and flower-driven cover) on insect predators and pests in Mediterranean vineyards. Relative abundance (%), defined as the "proportion of collected insects from each study's taxa of the total number," was used to compare the effect by ANOVA. They found that the cover crop vegetation increased beneficial insects such as carabids and forficulids. The spontaneous cover vegetation increased the abundance of ground beetles and the carnivorous genus *Nebria*, indicating management of spontaneous cover vegetation is the most important for conservation biological control.

5.2.1.7 Vibrational Signals

Korinsek et al. (2016) proposed one unique approach for pest control, which used species- and sex-specific substrate-borne vibrational signals. They analyzed the male and female leafhopper mating calls and proved the concept of using the audio signal for developing an insect trap.

5.2.1.8 Precision Spraying

Many studies were conducted for precision chemical spraying for efficient insect pest control. Kang et al. (2011) developed a laser-based trunk size detection system to precisely spray barriers for cutworms in vineyards. A 40 Hz laser sensor was installed on both sides of a small trailer with three different nozzles to achieve variable rates depending on the trunk size. In a field trial, they reported about 5 mm error in trunk radius estimation at five different travel speeds and average targeted spray efficiencies of 65–71% with 90–91% cost savings compared to typical application.

Escola et al. (2013) developed a variable rate sprayer using a LiDAR sensor for canopy volume measurement, a controller for determining spray rates, and electromagnetic variable valves as actuators for tree fruit orchards. They compared the algorithm determined and actual spray rates and found a strong relationship with a coefficient of determination of 0.94.

Gil et al. (2013) developed a similar variable rate sprayer using ultrasonic sensors, variable rate electro valves, and a controller for vineyards. They tested the sprayer at Merlot and Cabernet Sauvignon vineyards and reported a good relationship between the algorithm determined and actual spray rates and 22% savings compared to a conventional application.

Adamides et al. (2014) investigated different interaction interfaces for a teleoperated vineyard sprayer tested by 30 different human operators. They tested a single camera and multiple camera systems and found that the multiple view system was more efficient in spraying and yielded fewer collisions with various obstacles but took more time to complete tasks than a single camera system. Further, Adamides et al. (2017) developed a semi-autonomous vineyard sprayer and investigated the human interface with a robotic system.

Using plant cell density (PCD, a ratio of near-infrared band over a red band), Roman et al. (2020) compared variable pesticide application rates in vineyards. They calculated the PCD from airborne multispectral images, used to estimate plant vigor and application rates. They reported pesticide savings of more than 25% compared to standard treatment.

Li et al. (2009) constructed an automatic sprayer for insects using binocular stereo-vision constructed from a single camera for other crops. In a laboratory environment, the system scanned sample plants from bottom to top to identify the location of artificial insects using depth information and sprayed them. However, no test results regarding spraying performance were reported in the study. Further, Li et al. (2015) utilized multifractals, defined as “an extension of fractals with multiple scales,” to identify small-sized insects like whiteflies in greenhouses. From their testing with paprika plants in a greenhouse, their proposed method yielded 87% of correct detection.

5.2.1.9 Bird Control

Bird control is another important aspect of pest control for orchards and vineyards.

Ampatzidis et al. (2015) developed an autonomous bird control system using UAVs, a wireless ground sensor network, wearable devices, and a cloud-based decision system. The system posed visual (with large size drone), audio (unique sound), and chemical (target spraying of methyl anthranilate, a bird irritant) threats to pest birds. Even though they simulated bird detection events, the developed system successfully created UAV flight paths to bird location, spot-sprayed chemicals, and turned on speakers autonomously. They pointed out that short flight time, insufficient sprayer size, chemical efficiency, and bird detection accuracy could be potential problems.

A multilayer artificial neural network was utilized to detect pest birds in vineyards (Dolezel et al., 2016). Their study focused on a few representative species to be more effective. Previously recorded sound of birds was used to identify the presence of a target bird using labeled features by the linear prediction coding (LPC) as input vectors of the neural network. They reported 89% detection accuracy for the European starling (*Sturnus vulgaris*) and emphasized that the network would be suitable for field implementation since it does not require high computing power.

Another study was conducted for pest bird control. Bhusal et al. (2017) developed a bird detection system for wine grapes using outdoor cameras installed at four corners of a field and a Gaussian mixture-based segmentation algorithm. The most common problem birds in wine grapes were starlings, robins, and finches. Bird tracking was implemented using the Kalman filter. They reported an 85% precision in detecting and counting birds in a 30 m × 30 m testing plot by comparing manual and algorithm counts. They reported that shape features were not very useful due to distortion by motion blurriness. They counted 89 incoming and 46 outgoing birds during 2 h in the morning in 6 days.

Then, Bhusal et al. (2018) implemented unmanned aerial vehicles (UAVs) in a 15,000 m^2 (about 3.8 acres) commercial vineyard to keep away birds (starlings and robins). They tested the system over 14 days with a 5-hour flight each day. Two UAVs (Matrice M600 Pro and Phantom 4, DJI Inc., China) were flown 3–6 m above the canopies. Using ANOVA, they compared the effectiveness of flying UAVs relative to when no drones were used and found a significant difference in the number of birds when UAVs were used (about 50% less number of birds). Their future study included detecting incoming birds and redirecting them away from the vineyards.

Further, Bhusal et al. (2019) adopted the convolutional neural network (CNN) using very high 4 K resolution images (3840 × 2160 pixels) to enhance bird detection. They observed that classification accuracy increased from 70% to 92% using super-resolution images, but a more reliable model would be needed.

5.2.1.10 Summary

In summary, various methods were used to detect and control pests in orchards and vineyards. Most of the methods focused on detecting and managing insect pests. More efforts will be needed to develop sensing technologies for other pests such as mites, nematodes, and vertebrates. More research and field experiments will be needed for actual field implementation by growers.

5.2.2 Emerging Technologies for Pests

Based on the National Grape Research Alliance (https://graperesearch.org/), some of their top research priorities are building improved mechanization and automation systems to enhance labor efficiency and improve pest and disease detection, modeling, and control systems. However, as Rieger (2019) reported, most vineyard sensing technologies are currently focused on meteorological and soil conditions and water status for irrigation. He also reported that machine learning and artificial intelligence (AI) are heavily used to assess data and develop decision support models.

Some studies for insect pest detection use traditional artificial neural networks (Fedor et al., 2009); however, the current explosion of AI applications started with AlexNet, developed by Krizhevsky et al. (2012). AI has been used to detect insect pests (Ding & Graham, 2016; Shen et al., 2018; Xia et al., 2018) and can be used to predict future infestation. Among many studies, Nam and Hung (2018) compared the performance of VGG16 and SSD (single-shot multibox detector) for detecting insects on sticky traps and found that SSD was better for identifying insects.

More recently, instead of manual crop scouting in citrus production, an automated insect detection system was developed using machine vision and AI for the Asian citrus psyllid (ACP), which is the vector of the devastating Huanglongbing (or citrus greening) disease for citrus (Partel et al., 2019). By implementing pneumatic tapping rods, as shown in Fig. 5.3, images of insects collected on a viewing board were acquired and were analyzed by two consecutive convolutional neural networks (YOLO v3 and then YOLO v1) to increase detection accuracy. After testing on 90 citrus trees, precision (accuracy) and recall (sensitiveness) were reported to be 80% and 95%, respectively.

Along with the development of mobile AI, smartphone apps will be available in the near future. Schumann et al. (2020) reported an accuracy of 89% for identifying pests, disease, and nutrient deficiencies using a smartphone app trained by a deep neural network. However, they noted that it would not replace traditional diagnostic lab methods soon. A startup company, Bloomfield Robotics (https://bloomfield.ai/), is developing a mobile sensor platform and implementing AI and robotics in vineyard management for monitoring vine growth and berry yield. Another company (Vayyar Ltd., Israel) seems to be of interest to us, which developed a sensor that can create high-resolution 3D images by measuring the radiofrequency reflectance of objects. Niu et al. (2020) utilized the sensor to detect nematodes in walnut leaves and reported a 72% accuracy for classifying nematode infestation levels.

An attempt has been made to replace high spatial resolution UAV images with satellite images for managing a vineyard. In a recent study by Sozzi et al. (2020), NDVI from two different imaging platforms, i.e., Sentinel-2 satellite and UAV, were compared for precision vineyard management. Images were acquired from 30 vineyards in France, and the spatial resolution was the same as 10 m for both Sentinel-2 and UAV (upscaled from its original 0.08 m). Sentinel-2 images detected the same degree of variability when no individual vine management is needed, and no inter-row grass is used in NDVI calculation.

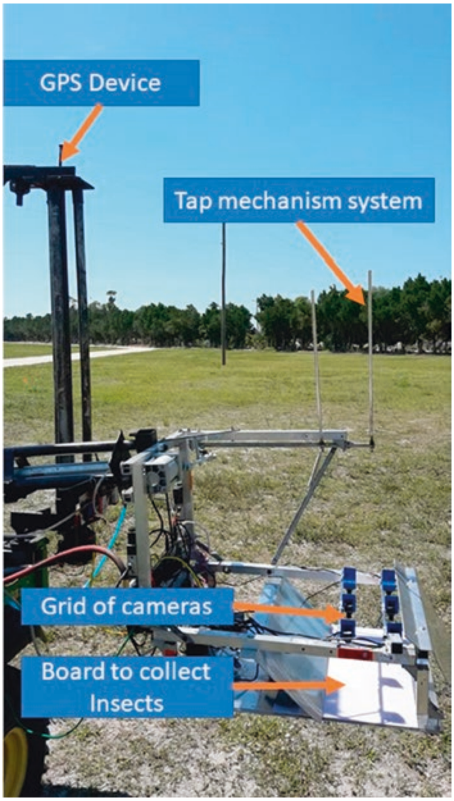

Fig. 5.3 Automated insect (Asian citrus psyllid) detection system. (Adapted from Partel et al., 2019)

A new integrated pest management (IPM) model (Fig. 5.4) was proposed by Dara (2019), which includes management, business, and sustainability aspects. The management aspect includes pest management, knowledge, resources for pest and technology, planning and data organization, communication among growers and the public, and research and outreach. In the business aspect, public education was emphasized for efficient IPM and traditional training for growers. In the sustainability aspect, conventional farming can be safer and more sustainable as long as IPM principles are emphasized, rather than organic farming, which is traditionally considered safe but can cause some "social inequality and a false sense of well-being."

A more precise spraying system was developed using a laser. Chen et al. (2019) tested a laser-guided intelligent sprayer in tree crop nurseries to investigate the efficiency of controlling insects and diseases. They found 52–56% of pesticide reduction and equal or a smaller number of insects (leafhoppers and aphids). A commercial sprayer is already available using this technology.

In predicting pest infestation, spatial interpolation using GIS and machine learning can be useful tools. While describing the IPM of mites, Liburd et al. (2019)

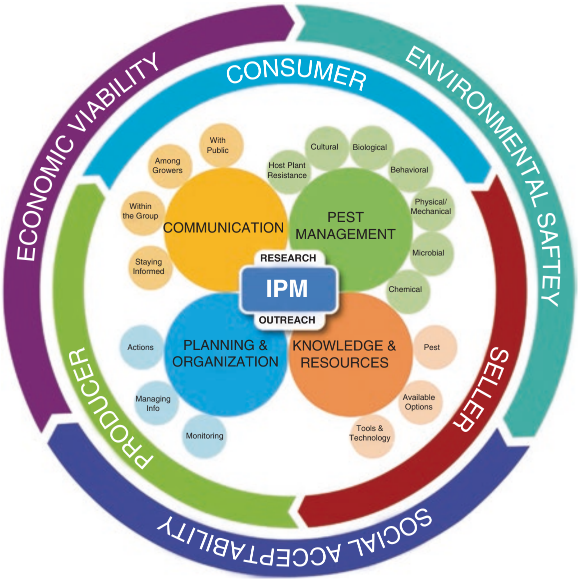

Fig. 5.4 A new model for integrated pest management. (Adapted from Dara, 2019)

suggested spatial interpolation of pest density using GIS to predict pests at unsampled locations in a field. This information can be used for site-specific spot spraying of insecticides. They expected that machine learning could be useful for identifying the distribution and infestation of pests and predatory insect species.

Overall, some new technologies have been developed and are currently being investigated for fruit orchards and vineyards. With more interest and support from growers, industries, and state and federal agencies, more effort will still be needed for pest detection and management.

5.3 Sensing and Actuation Technologies for Plant Diseases

Advanced technologies can also be applied for detecting plant diseases in agriculture with several advantages versus conventional methods. Emerging technologies can be used for quantitative and qualitative evaluation of plant diseases (Ali et al., 2019; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010).

Visual symptoms of infected plants can be evaluated by optical sensors directly in the field using computer vision sensors mounted on the ground and aerial platforms. However, visual symptoms assessment is a conventional first step for plant disease diagnosis. Still, it fails to detect a pathogen in early infection stages when plant infections are asymptomatic. Early detection of plant pathogens can be very important for crop health monitoring. It allows for optimized crop protection in the field during different stages and minimizes the risk of the spread of disease infections and reduces spray treatments. Indeed, early detection of plant disease is needed in agriculture to reduce the economic and environmental impact. Hyperspectral sensors are shown as one of the most powerful technologies for early disease detection in agriculture (Mahlein et al., 2018, 2019; Thomas et al., 2018). Moreover, machine learning and recently deep learning have been successfully developed and applied in phytopathology to make a prediction from data and to improve the decision-making process in crop protection (Zhu et al., 2017; Mahlein et al., 2019; Polder et al., 2019; Sladojevic et al., 2016) in the context of precision farming.

5.3.1 State-of-the-Art Sensing and Actuation Technologies for Plant Diseases

In agriculture, diseases in plants are typically verified using several conventional methods. Traditionally, plant disease incidence is assessed by the interpretation of visual symptoms. Visual assessment and culturing are subjective methods and require trained personnel and considerable time to complete a diagnosis. Other current and conventional methods were based on the laboratory analysis of samples collected in the field, manually at a single plant. Enzyme-linked immunosorbent assays (ELISA), immunology-based methods, polymerase chain reaction (PCR), and real-time PCR (RT-PCR) can be used for plant disease detection (Fang & Ramasamy, 2015; Ray et al., 2017). These methods are time-consuming and require complex and expensive instruments, which are not appropriate for infield operation. A summary of the advantages and limitations of these methods is shown in Table 5.1. All these lab methods were precise with high accuracy for plant pathology diagnosis; however, they required collecting plant samples before wet chemistry analysis, limiting their infield applications. Consequently, there is strong interest in developing new and reliable technologies for plant disease detection under field conditions.

Table 5.1 Current and conventional methods in plant disease detection

Method	Advantages	Limitations
Visual assessment	Easy to operate	Subjective Time-consuming Trained personnel
Culturing methods	Cheap and simple	Non-rapid Subjective Trained personnel
Isoenzyme analysis	Precise and rapid	Low level of polymorphism in fungi Not suitable for infield operation
Immunology-based methods	Accurate	Low sensitivity Not suitable for infield operation
Polymerase chain reaction (PCR)	High accuracy and sensitivity	Expensive Not suitable for infield operation

The above methods for plant disease detection have been mainly applied in research, breeding, and phenotyping; however, they are not suitable for infield operation. The applications of these lab methods in commercial agriculture have been limited. Currently, new techniques for rapidly and cost-effectively assessing diseases in vineyards and fruit orchards are needed.

5.3.2 Emerging Technologies for Plant Diseases

New sensors and technologies can be used to evaluate crop status quickly and inexpensively. New technologies can assess plant diseases with reliability, precision, and accuracy (Mahlein, 2016; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010). It is important to emphasize that the non-destructive nature of many of these technologies implies the absence of damage or any modification of the plant material under analysis. Some of the main non-invasive detection technologies used for crop monitoring include computer vision, thermography, spectroscopy, chlorophyll fluorescence, and multi- and hyperspectral imaging.

These sensing technologies can be implemented in portable sensors. However, they can also be mounted on vehicles such as quads, tractors, or robots and even aerial platforms such as drones, aircraft, or satellites. Proximal and remote sensing technologies are playing an increasingly prominent role in modern agriculture, making it easier to gather data quickly and affordably. Furthermore, the new and powerful non-invasive sensors can obtain georeferenced information in most cases. It is possible to generate maps of the different parameters and establish zones that require different management practices within precision agriculture.

5.3.2.1 Plant Volatile Organic Compounds

Recently, it was suggested that plant volatile organic compounds could be used in agriculture to improve crop defense strategies (Brilli et al., 2019). The pathogen-plant interaction could result in the release of specific volatile organic compounds that highly indicate the plant disease (Fang et al., 2014; Fang & Ramasamy, 2015; Ray et al., 2017). Gas chromatography combined with mass spectroscopy has been used for analyzing volatile organic compounds emitted by diseased plants (Fang & Ramasamy, 2015). However, before analyzing the volatile compounds by gas chromatography, several complex strategies and procedures for obtaining these volatile compounds from a single plant should be defined and performed (Tholl et al., 2006). This technique has been used for detecting fungal diseases in various plants (Fang et al., 2014; Vikram et al., 2006).

Nowadays, plant volatile compound analysis is time-consuming and requires a pre-sampling manually in the field, so infield application was very limited. Several recent reviews have discussed the different strategies for monitoring volatile compounds for plant disease detection (Sankaran et al., 2010; Fang & Ramasamy, 2015; Martinelli et al., 2015).

5.3.2.2 Biosensors

Biosensors are a novel diagnostic tool for detecting plant diseases. On-site detection of plant pathogens can be performed using biosensors. Integration of different techniques in portable devices led to the development of biosensors. Table 5.2 summarizes the main biosensors used to detect numerous fungal pathogens. Biosensors used in plant disease detection have been recently reviewed by Ray et al. (2017). Biosensors are gaining much interest for detecting fungal plant diseases and can be a promising alternative tool in crop protection. Some recent reviews have described the strategies of the different biosensors for detecting plant diseases (Ray et al., 2017; Khater et al., 2017). Several biosensors based on different techniques are commercially available to detect several plant pathogens such as *Phytophthora*, *Pythium*, *Oidium*, and *Botrytis cinerea* (Ray et al., 2017; Khater et al., 2017). Commercial biosensors are portable small/pocket devices for detecting diseases at the leaf or plant level, and they can be used under lab or field conditions (Khater et al. 2017).

Table 5.2 Main biosensors used in plant fungal pathogen detection

Type of method	Biosensor	Pathogen
Optical biosensors	Fluorescence-based biosensors	*Phytophthora palmivora*
	Chemiluminescence-based biosensors	*Saccharomyces cerevisiae* *Hansenula anomala*
	Surface plasmon resonance (SPR)-based biosensors	*Phytophthora infestans*
Volatile biosensors	Electronic nose system	*Botrytis* sp. *Penicillium* sp.
	Field asymmetric ion mobility spectrometry (FAIMS)	*Oidium neolycopersici*
Electrochemical biosensors	Amperometric platform	*Saccharomyces cerevisiae* *Cerrena unicolor*
	Potentiometric platform	*Lentinus sajor-caju*
	Impedimetric platform	*Phakopsora pachyrhizi* *Penicillium sclerotigenum*
	Conductometric platform	*Candida albicans*, *Aspergillus niger*
Mass-sensitive biosensors	Quartz crystal microbalance (QCM) biosensors	*Candida albicans* *Candida glabrata*
	Cantilever-based biosensors	*Aspergillus niger* *Saccharomyces cerevisiae*
Point-of-care (POC) tests	Lateral flow assays (LFAs)	*Phytophthora* species
	Microfluidic paper-based analytical devices (μPADs)	*Botrytis cinerea* *Peronospora destructor*
Nanomaterial-based biosensors		*Aspergillus niger* *Metarhizium anisopliae*

Adapted from Ray et al. (2017)

5.3.2.3 Non-destructive/Non-invasive Sensing Technologies

Non-destructive/non-invasive sensing technologies are gaining much interest for detecting plant diseases and can be a promising alternative tool in crop protection. Non-destructive/non-invasive (both terms are interchanged, generally) techniques are defined as methods that do not alter the physical state of an object. These technologies have been successfully implemented to measure some important physiological parameters in non-invasive ways. Non-invasive sensing technologies are associated with remote and proximal sensing, which acquire information from the plant-pathogen interaction. Most of these technologies are based on the interaction between electromagnetic radiation and the plant. The electromagnetic spectrum provides information about plant physiological status, and consequently, an infected plant generally displays a different spectral signature to that of a healthy plant (Ali et al., 2019; Delalieux et al., 2007; Sankaran et al., 2010).

Non-destructive technologies used for detecting plant diseases were reviewed by several authors (Ali et al., 2019; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010; Thomas et al., 2018). Table 5.3 summarizes non-invasive sensing technologies employed for detecting diseases in vineyards and tree fruit orchards. Non-invasive technologies include fluorescence, thermography, X-ray, spectroscopy, computer vision, multispectral imaging, and hyperspectral imaging. They were applied in grapevine, citrus, apple, pear, avocado, kiwifruit, raspberry, etc. Numerous important crop pathogens and diseases such as citrus greening disease (Huanglongbing), citrus canker (*Xanthomonas citri*), apple scab (*Venturia inaequalis*), phytophthora root rot disease, downy mildew (*Plasmopara viticola*), powdery mildew (*Erysiphe necator*), *Botrytis cinerea*, Flavescence dorée, grapevine leafroll disease, and grapevine trunk diseases (GTD) were detected using non-invasive technologies.

Non-invasive sensing technologies can be integrated into portable devices and ground and aerial platforms, as discussed in the next section. Some technologies are commercially available for disease detection in grapevine and fruit trees, while others are being developed.

5.3.2.4 Hyperspectral Imaging

Hyperspectral imaging (HSI) is one of the most powerful non-invasive technologies. Hyperspectral imaging has been applied in agriculture, forestry, environment, defense, medicine, water, food quality, and safety control. Spectral resolution (narrower wavelengths) and the band number are the key features that characterize HSI. Hyperspectral imaging provides one full spectrum for each pixel of the collected image. Hyperspectral sensor and imaging techniques have shown a great potential for detecting plant diseases. Several authors have recently reviewed HSI applications in phytopathology (Mahlein et al., 2018, 2019; Thomas et al., 2018). Specific spectral indices can be developed for disease detection and monitoring in precision agriculture (Mahlein et al., 2013).

Table 5.3 Non-invasive sensing technologies for detecting diseases in apple trees, citrus, grapevine, and tree fruit plants

Technology	Plant	Disease/pathogen	References
Fluorescence	Citrus	Citrus canker (*Xanthomonas citri*)	Belasque et al. (2008) and Lins et al. (2009)
	Grapevine	Powdery mildew (*Erysiphe necator*) Downy mildew (*Plasmopara viticola*) Downy mildew (*Plasmopara viticola*)	Bélanger et al. (2008), Cséfalvay et al. (2009) and Latouche et al. (2015)
Thermography	Apple	Apple scab (*Venturia inaequalis*)	Oerke et al. (2011)
	Kiwifruit	Pseudomonas syringae pv. actinidiae (Psa)	Maes et al. (2014)
	Grapevine	Downy mildew (*Plasmopara viticola*)	Stoll et al. (2008)
	Olive tree	*Verticillium*	Calderón et al. (2013)
X-ray	Raspberry	*Botrytis cinerea*	Goodman et al. (1992)
	Grapevine	Grapevine trunk disease (GTD)	Vaz et al. (2012)
Spectroscopy	Apple	Apple scab (*Venturia inaequalis*)	Delalieux et al. (2007)
	Citrus	Anthracnose	Blasco et al. (2007)
	Grapevine	Grapevine leafroll disease Grapevine trunk disease (GTD)	Naidu et al. (2015) and Levasseur-Garcia et al. (2016)
Computer vision	Apple	Apple scab (*Venturia inaequalis*)	Wijekoon et al. (2008)
	Citrus	Anthracnose	Blasco et al. (2007)
	Grapefruit	Greasy spot (*Mycosphaerella citri*), melanose (*Diaporthe citri*), and scab (*Elsinoe fawcettii*)	Pydipati et al. (2006)
	Avocado	Phytophthora root rot disease	Salgadoe et al. (2018)
	Grapevine	Powdery mildew (*Erysiphe necator*)	Oberti et al. (2014)
Multispectral imaging	Citrus	Citrus greening disease (Huanglongbing)	Kumar et al. (2012)
	Grapevine	Grapevine leafroll disease (GLD) Flavescence dorée *Armillaria*	Hou et al. (2016) and Albetis et al. (2017) Candiago et al. (2015)
	Olive tree	*Verticillium*	Calderón et al. (2013)
Hyperspectral imaging	Apple	Apple rottenness (*Penicillium*)	Zhang et al. (2015)
	Pear	Pear black spot disease (*Alternaria alternata*)	Pan et al. (2019)
	Citrus	Citrus canker (*Xanthomonas citri*) Citrus greening disease (Huanglongbing) Citrus greening disease (Huanglongbing)	Qin et al. (2008), Lee et al. (2008) and Moriya et al. (2019)
	Grapevine	Downy mildew (*Plasmopara viticola*) Powdery mildew (*Erysiphe necator*)	Oerke et al. (2016) and Pérez-Roncal et al. (2020)

Table 5.4 Hyperspectral imaging (HSI) applications in grapevine and fruit tree orchards

Plant	Imaging conditions	Disease/pathogen	References
Citrus	Field	Citrus greening disease (Huanglongbing)	Moriya et al. (2019)
Pear	Laboratory	Pear black spot disease (*Alternaria alternata*)	Pan et al. (2019)
Apple	Laboratory	Apple rottenness (*Penicillium*)	Zhang et al. (2015)
Olive	Field	*Xylella fastidiosa*	Zarco-Tejada et al. (2018)
Grapevine	Laboratory	Downy mildew (*Plasmopara viticola*)	Oerke et al. (2016)
Grapevine	Laboratory/field	Downy mildew (*Plasmopara viticola*)	Poblete-Echeverría & Tardaguila, (2023)
Grapevine	Laboratory	Powdery mildew (*Erysiphe necator*)	Pérez-Roncal et al. (2020)

Table 5.4 summarizes HSI applications in grapevine and fruit tree orchards. HSI was employed in citrus, pear, apple, grapevine, etc. Several important plant pathogen diseases such as citrus greening disease (Huanglongbing), pear black spot disease (*Alternaria alternate*), apple rottenness (*Penicillium*), downy mildew (*Plasmopara viticola*), and powdery mildew (*Erysiphe necator*) were detected under laboratory and field conditions.

Hyperspectral imaging is a powerful technology, but it has been typically used under laboratory conditions. Very few attempts at infield hyperspectral imaging have been reported in the literature, due to the difficulties, such as natural and irregular illumination or unknown a priori sample positioning in the recorded scene, that are necessary to face.

Gutiérrez et al. (2018) have used HSI as a ground platform for grapevine phenotyping on the go. This study acquired hyperspectral images under natural illumination with a VIS-NIR hyperspectral camera (400–1000 nm) mounted on an all-terrain vehicle moving at 5 km/h in a commercial Tempranillo vineyard in Spain (Fig. 5.5). The same mobile hyperspectral sensing ground platform could be used for disease detection in commercial vineyards (Tardaguila et al. unpublished data). HSI sensor was also mounted into aircraft for detecting citrus greening disease (Huanglongbing) in Brazil (Moriya et al., 2019). *Xylella fastidiosa*, one of the most dangerous plant pathogens, was detected at the previsual stage in the olive orchard by hyperspectral and thermal sensors mounted in an airborne (Zarco-Tejada et al., 2018).

5.3.2.5 Sensing Platforms and Robots

Plant disease detection could be performed by integrating non-invasive sensing technologies into different platforms: portable devices (apps, smartphones, etc.), ground platforms (quads, tractors, robots, etc.), and aerial platforms (drones, aircraft, etc.) and satellites. Emerging technologies can be used for quantitative and qualitative evaluation of plant diseases (Ali et al., 2019; Mahlein et al., 2019; Ray

Fig. 5.5 Hyperspectral imaging camera mounted on an all-terrain vehicle moving at 5 km/h used for monitoring a commercial vineyard in Spain. (Photo: Javier Tardaguila)

Table 5.5 Sensing platforms for detecting diseases in vineyards and tree fruit orchards under field conditions

Platform	Plant	Disease/pathogen	References
Portable	Avocado tree	Phytophthora root rot	Salgadoe et al. (2018)
Ground platforms	Grapevine	Downy mildew Grapevine trunk diseases (GTD)	Tardaguila et al. (unpublished data)
Drone/UAV	Grapevine Grapevine Grapevine Citrus	Flavescence dorée Grapevine trunk diseases (GTD) *Armillaria* Citrus greening disease (Huanglongbing)	Albetis et al. (2017) Albetis et al. (2019) Candiago et al. (2015) and Garcia-Ruiz et al. (2013)
Aircrafts	Olive Citrus Citrus	*Xylella fastidiosa* Citrus greening disease (Huanglongbing) Citrus greening disease (Huanglongbing)	Zarco-Tejada et al. (2018) Garcia-Ruiz et al. (2013) and Moriya et al. (2019)
Satellites	Citrus	Citrus greening disease (Huanglongbing)	Li et al. (2015)

et al., 2017; Sankaran et al., 2010). The potential of aerial platforms to evaluate biotic and abiotic stress factors in precision agriculture has been recently reviewed (Sankaran et al., 2015). Table 5.5 summarizes sensing platforms that have been used for disease detection in vineyards and tree fruit orchards.

Phytophthora root rot incidence was assessed in an avocado orchard using RGB images taken by a smartphone camera. Visual symptoms of downy mildew and grapevine trunk diseases (GTD) in commercial vineyards were evaluated and mapped using an RGB sensor mounted on a mobile sensing platform at 5 km/h (Tardaguila et al. unpublished data).

Several diseases were detected in vineyards and citrus orchards using different remote sensing technologies integrated on aerial platforms such as drones or UAVs (Albetis et al., 2017; Albetis et al., 2019; Candiago et al., 2015; Garcia-Ruiz et al. 2013) and aircraft (Garcia-Ruiz et al., 2013; Moriya et al., 2019; Zarco-Tejada et al., 2018). Additionally, citrus greening disease (Huanglongbing) was detected using multispectral satellite information (Li et al., 2015).

The development and use of robotics can greatly facilitate the application of precision crop protection in the future, as it makes autonomous and continuous surveillance of the vineyards and orchards possible and optimizes any subsequent automated intervention based on the information obtained.

Sensing platforms offer the potential to map disease incidence in the plot. It can allow differential fungicide application using variable-rate technology. These new technologies will improve sprays' timing and volume, reducing agronomical damage, economic losses, and environmental impact.

5.3.2.6 Artificial Intelligence for Crop Protection

New technologies, sensor systems, artificial intelligence, and automation will be the key to the agriculture of the future. Artificial intelligence is a revolution at different work and industrial levels to deal with data. Machine learning has evolved greatly within artificial intelligence during the last decades, providing tools to make computers learn. These algorithms are used in many fields due to their high versatility for any data-related tasks, generating knowledge and information, and improving the decision-making process (Gutiérrez, 2019).

Advances in non-invasive sensing technologies allow the acquisition of high amounts of data from the vineyard. Still, these data alone are not enough to be used when decisions need to be made, and they need to be transformed into actionable information. Therefore, the combination of non-invasive sensors and artificial intelligence needs to be applied to meet the requirements needed to apply digital agriculture and data-driven agriculture.

Data are the key to disease diagnosis and decision-making in vineyards and fruit orchards (Mahlein, 2016; Mahlein et al., 2019). Artificial intelligence, machine learning, and big data will help the growers of the future to make decisions and optimize the crop protection management of their vineyards to meet their established objectives, providing useful information both in the vineyard and fruit orchards (Mahlein et al., 2019; Gutiérrez et al., 2018). The combination of data from different sources of soil-plant-environment could be important to obtain information and make forecasts to optimize crop protection management, leading to sustainable agriculture.

5.4 Conclusions

Many new technologies have been developed and are currently being investigated for fruit orchards and vineyards for managing pests and diseases. New technologies can be applied to crop protection. New reliable, objective, rapid, and field-deployable crop disease and pest detection methods are needed. Artificial intelligence and new non-invasive technologies will help growers in the future to make decisions and optimize fruit orchards and vineyard management in line with set targets. Combining data on both the plant and environmental factors will be important in obtaining useful information and making predictions that can optimize pest and disease management and hence sustainable vineyards and tree fruit orchards. Even though many new technologies have been developed and applied to crop production, more effort will still be needed, especially for disease and pest management, with more interest and support from growers, industries, and state and federal agencies.

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