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Developments in crop insect pest detection techniques

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1 Introduction

To meet the challenges agriculture faces now on a planet buffeted by climate change (Skendžić et al., 2021) requires organized efforts across its production and research sectors (Botha et al., 2014; Xia et al., 2022) to minimize food scarcity and reduce environmental and human health impacts (Frye et al., 2012) while conserving dwindling resources (Jordon et al., 2021). Part of this effort involves early detection and identification of targeted pests (Fedor et al., 2009; Lima et al., 2020) to avoid increases in pre- and post-harvest losses and economic harm expected from global warming (Deutsch et al., 2018). Problems of food scarcity are exacerbated because humans have higher metabolic rates than most animals of the same size (Gibbons, 2022) and thus must consume relatively more high-energy food.

An ideal insect-detection system for integrated pest management (IPM) accurately identifies and spatially targets pests early in their life cycles (Thenmozhi and Reddy, 2019; Liu and Wang, 2020) and is affordable relative to the value of

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the crop being protected, especially when considering the economic needs of the farmer, the impacts of management practices on neighboring and regional farms, and regulatory requirements at local and regional levels (Dara, 2019; Singerman and Rogers, 2020). Because cropland management units have different sizes, the distances over which insect pests are detected by a particular technology can affect their relevance to the data collection needs of farmers and pest managers, as well as government officials who have responsibility for regulatory and conservation oversight in regions adjacent to the croplands. There remains a considerable need for research on conservation in landscape habitats surrounding crops (Karp et al., 2018), especially with respect to edge effects in fragmented habitats (Laurance et al., 2018). A better understanding of predator and parasitoid abundance and behavior in such areas can help resolve uncertainties about best management practices. Fortunately, as discussed in different sections later, growers and pest managers have access to increasingly affordable, complementary insect-detection technologies, i.e. physical- and biochemical-energy detection tools augmented by artificial intelligence (AI) (Partel et al., 2019; Cheng et al., 2022) that makes use of machine learning and deep learning methods (LeCun et al., 2015; Karar et al., 2021; Roch et al., 2021) incorporating convolutional neural networks (Thenmozhi and Reddy, 2019; Spiesman et al., 2021) to quickly recognize patterns in images, acoustic recordings, and other detected signals which enable identification of pest insects. For purposes of this chapter, applications of complementary technologies to insect detection in agriculture first became available with the development of remote visual and radar sensing after the 1940s (Riley, 1989; Reynolds et al. 2005) and accelerated after 1983 when the Global Positioning System was made available for public use (Comparetti, 2011).

Traditional field surveys of pest insects by farmers and scouts, as well as observations of search activities by insect predators and parasitoids that can serve as survey proxies, are being combined with input from recently developed insect behavioral and sensory detection technology, computer-based pest identification, and rapidly improving knowledge of pest-insect host-seeking and feeding behaviors to enhance the effectiveness of pest management activities (Table 1). An example of such combinations is the inclusion of electronic sensors in pheromone traps. Pheromones and other semiochemicals such as kairomones, allomones, and antifeedants (Norin, 2007; Murali-Baskaran et al., 2018) are volatile organic chemicals (VOCs) or contact chemicals which influence behaviors of insects and other animals that sense them. Physiological correlates of such behaviors have been explored by examining neurophysiological signals in the insect central nervous systems antennae, eyes, and mechanoreceptor sensory organs. Of particular interest with respect to insect behavior, electroantennograms (EAGs) (Olsson and Hansson, 2013; Martinez et al., 2014) detect insect antennal electronic responses to

Table 1 Enhancements of traditional methods with complementary technologies for detecting and managing crop insect pests

Traditional sensing methods	Complementary technologies
Vision	Sensors of electromagnetic energy (light, heat, radar, X-ray, etc.) (additional coverage in other chapters of this book)
Audition touch/vibration	Sensors of sound/vibration energy
Taste/smell	Biochemical/molecular/nanobionic/electrophysiological sensors identifying DNA fragments, metabolites, and contact or volatile organic chemicals, electrical penetration graphs (additional coverage in other chapters of this book)
Observation of predator/parasitoid searching behavior activities	Smart traps, mating disruption, pest exclusion, push-pull, refuge plants (additional coverage in other chapters of this book)

volatiles. Electroretinograms (ERGs) (Yinon, 1971; Stowasser et al., 2015) detect retinal electronic responses to light of different wavelengths. Mechanoreceptors (Tuthill and Wilson, 2016) detect substrate vibrations and insect movements.

The combined usage of traditional methods and complementary technology is expanding rapidly. Attractant-baited 'smart' automated traps (Jiang et al., 2008) are now easily fitted with digital red/green/blue ((RGB) wavelength) cameras and piezoelectric or fiber optic acoustic/vibration sensor systems that enable rapid wireless transmission of information to remote data sites. Internet of things (IoT) technology (Potamitis et al., 2017; Rigakis et al., 2021a) connects and analyzes information collected by these sensor networks, enabling rapid processing and delivery of the sensor data back to farmers and other pest managers (Karar et al., 2022). The data they collect can be organized into easily interpreted formats that are superimposed on real-world displays, i.e. augmented reality (Huuskonen and Oksanen, 2018), helping farmers and managers interpret the data collected. Other technologies are used primarily in research at this time but may be adapted for field use in the future.

Typical detection ranges of traditional methods and complementary technology can be subdivided spatially along nano-, micro-, meso-, and macro-scales (Table 2). Nano-scale technology utilizes multiple biochemical tools and nanobionic sensors (Ang and Lew, 2022) operating internally in insect organs, including genetic marker-based analyses which can help distinguish among strains of a pest insect species that have similar morphologies but different host preferences and different levels of pesticide resistance, e.g. Nagoshi et al. (2017). Detection ranges in the micro-scale region include those of visual, auditory, vibrational, and olfactory sense organs which operate from a few millimeters to a few meters distance from the pest insect. In this range, sensors can be used for the detection of insects on individual crop plants or trees.

Several methods used to detect crop insect pests in the micro-scale range also have been applied in the detection of fruit damage during harvesting and later stages of the food supply chain (Mahanti et al., 2022). Such technologies have also been applied to assess the structural characteristics and health of plants (Mankin et al., 2018) and to detect disease vectors like mosquitoes or pollinators through wingbeat detection (Chen et al., 2014; Jakhete et al., 2017).

The meso-scale (Table 2) corresponds to the detection range of several radars, typically 2.5 km for individual insects or up to 10 km or more for insect swarms at dense concentrations (Riley, 1989). Vertical-entomological radars are regularly monitored in the United Kingdom (Chapman et al., 2010; Hu et al., 2016) to determine the timing and sizes of large-scale migrations. Meso-scale technology also includes weather radar, which Stepanian et al. (2020) used to detect airborne mayfly swarms. Drones and small airplanes with digital cameras are deployed to detect insects or insect-initiated damage over meso-scale ranges and, depending on height, can detect 1–10 cm-width objects

Table 2 Spatial scales of insect-detection technologies

Detection range	Traditional methods	Complementary technology
Nano-scale (<1 mm)	Biochemical/molecular	Single nucleotide polymorphisms, nanobionic sensors (additional coverage in other chapters of this book)
Micro-scale (<1 m)	Vision/Audition/Touch	Hand-held, stationary, or drone red/green/blue wavelength cameras (additional coverage in other chapters of this book) acoustic/vibration sensors, electrical penetration graph, or laser vibrometer systems for pest detection within crop plants, trees, and stored products
Meso-scale (<1 km)	Electroantennogram/electroretinogram/single olfactory cell electronics/smell/sound recorders Radar	Multicellular electrophysiological recordings of volatile organic chemicals drone/airplane-cameras multispectral scanning (additional coverage in other chapters of this book)
Macro-scale (>1000 km)	None	Satellite weather/behavior-based dispersal models (additional coverage in other chapters of this book)

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on the ground (Huuskonen and Oksanen, 2018; Iost Filho et al., 2020). Lidar (Brydegaard and Jansson, 2019; Tauc et al., 2019) and similar devices using near-infrared light-emitting diodes (LEDs) (Rydhmer et al., 2022) operate at micro- and meso-scale detection ranges. The LED systems can be used as pseudo-acoustic sensors to reflect light from the wings of flying insects and analyze the time-varying reflections from beating wings (Chen et. al., 2014; Rydhmer et al., 2022). These have become useful tools for electronically collecting information from pheromone traps (Table 1).

The macro-scale encompasses landscapes that can be examined by satellites, which resolve objects on the ground with dimensions of 30 m (Huuskonen and Oksanen, 2018; Bright et al., 2020). Insects cannot be individually resolved at this scale, but satellites provide a series of Landsat images of specific regions that can be analyzed to identify areas of crops impacted by insect damage (Bright et al., 2020). Meso- and macro-scale technologies are two of the several methods for the remote detection of insect pests Riley (1989).

Traditional methods of insect monitoring continue as important pest management tools (Tables 1 and 2), but the accuracy of population forecasts is often dependent on dwindling expert knowledge (Zhang et al, 2019; Furuya et al., 2021). Farming operations could benefit from additional data obtained using newer insect-detection, AI, and IoT technologies (Osco et al., 2022) although concerns over ownership (Yu et al., 2021) and security (Alahmadi et al., 2022) of obtained data remain to be clarified. Moreover, traditionally developed knowledge of VOCs, visual, and auditory stimuli that affect feeding and mating behaviors of crop pests has been applied to augment pest control measures (Foster and Harris, 1997; Čokl and Millar, 2009; Davis et al., 2013; Silva et al., 2021). Recent improvements in technologies associated with formulation and dissemination of VOCs, and additionally, technologies associated with molecular biology, nanobionics, electronics, acoustics, and computer technology have benefited understanding of how pest insects detect and use VOCs and vibrational signals, and how these stimuli can be co-opted for pest management. Examples of recent applications of such technology are listed in Table 3. It should be noted for the last entry of Table 3, however, that care must be exercised in the broadcasting of sounds that disrupt mating to ensure that the signals remain below levels of urban noise pollution implicated as one of the potential causes for declines in nonpest invertebrate populations (Goulson, 2019; Raboin, 2021).

This chapter is arranged approximately according to sensory modality (visual, acoustic, vibration, olfaction, etc.) with consideration of how each modality is used in insect pest detection and management activities at different scales of detection.

Table 3 Examples of complementary technology in pest management activities that involve sensing and/or co-opting of stimuli used by pest insects for communication

Technology/Application	References
Enhanced use of volatile organic chemicals for pest insect mating disruption	Miller and Gut (2015); Preti et al. (2021); Higbee and Burks (2021); Gavara et al. (2022)
Seasonal monitoring of regional nonpest species co-attracted to pheromone traps detecting Plusiine pests	Shaw et al. (2021)
Kairomones for biological control	Martini et al. (2014); Murali-Baskaran et al. (2018); Da Silva et al. (2022)
Kairomone-enhanced pheromone lures	Walgenbach et al. (2021)
Floral scent real-time sampling	Kim et al. (2022); Zheng and Zhang (2022)
Electroantennograms and single olfactory cell recordings to determine the temporal patterns of emission and active spaces of natural or synthetically produced volatile organic chemicals	Mayer et al. (1987); Suckling et al. (2007); Mankin et al. (1991); Yang et al. (2022)
Broadcast of sound or vibrations for insect pest mating disruption	Polajnar, et al. (2015); Lujo, et al. (2016); Laumann et al. (2018); Takanashi et al. (2019); Mazzoni et al. (2019); Avosani et al. (2022)

2 Camera systems for pest detection at micro-scale ranges

Moth pheromone traps were initially expected to selectively capture a single species, but experience demonstrated that some pheromones captured insects of multiple, closely related species depending on the geographical region. Camera systems were later incorporated to send images of trapped insects to remote locations where individuals of each caught species were identified and counted by computer analyses or by human identification (Guarnieri et al., 2011). However, it became apparent that fully automated approaches were needed to discriminate among the large numbers of different species captured in multiple regions where trapping was used as a detection tool. In addition, general scouting operations could benefit from the automated identification of insects photographed during surveys. Consequently, collections of multiple datasets with large numbers of images of different insect species and stages, including the Indian Council of Agricultural Research and the National Bureau of Agricultural Insect Resources dataset (Karar et al., 2021) were analyzed for specific features to distinguish among species. Machine learning algorithms were developed (Karar et al., 2021) that identified images of important insect crop pests independently of orientation (Deng et al., 2018: Thenmozhi and Reddy, 2019). Similar collections were developed for other pests worldwide, including VisDrone-VDT2018 with 80 000 drone-collected images of insect pests (Zhu et al., 2019), PlantDiseaseNet, with 79 275 pest images collected under various meteorological conditions (Liu and Wang, 2020), IP102 (Wu et al., 2019), with 75 000 images belonging to 102 pest categories, Xie2 (Xie et al., 2018) with 4000 images of different pest species, and APHID-4K with 4000 images of aphids (Du et al., 2021), who also developed machine learning methods to detect images of aphid clusters. The individual aphids could not be distinguished from each other due to the limited resolution of the camera. Kasinathan et al. (2021) combined several machine learning techniques to classify and detect insects in digital camera images collected in corn, soybean, and wheat fields.

Deep learning methods usually require access to more data than machine learning due to a larger number of neural network layers that must be calibrated. However, they have been used successfully with several of the largest data sets above to classify crop insect pest species. Li et al. (2021), for example, describe the use of deep learning methods to analyze images collected from immatures and adults of ten crop pest species obtained from Bing, Pest24, TPest, and AgriPest.

Several camera-based pest insect detection systems are listed in Table 1. When applying such technology to insect detection, there is a need to recognize the variability of insect morphological characteristics of the same species in different orientations at different life stages. When trapped insects are imaged, discoloration by liquid trapping agents, loss of legs, insect clumping, and debris introduce specific features that cannot be incorporated into the identification process unless such images are also included in the training dataset (Nanni et al., 2022).

Complementary technologies that have been tested but are not yet in common usage include a guarded electrical probe developed by Thomas et al. (2021) to measure electrical impedance. The device was used in experiments to noninvasively identify stalks of maize, *Zea mays* L., that had been partially hollowed out by *Ostrinia nubilalis* Hübner (Lepidoptera: Pyralidae) larvae. In an earlier approach, Labatte et al. (1992) applied X-ray imaging methods to map cavities produced within maize plants by *O. nubilalis* feeding behaviors.

3 Drone/camera systems for pest detection at meso-scale detection ranges

Uses of small drones for IPM in a variety of crop pest insect applications are reviewed by Iost Filho (2020). Drone systems are particularly useful for preparing digital maps of pest insect ‘hot spots’ that can be precisely targeted for treatment. One example of RGB-camera-based technology to detect crop insect pests (Kalischuk et al., 2019) involved assessments of insect pest damage that caused increases in plant disease severity and plant stress. Testing was conducted in watermelon fields comprising 15–38 ha, using DJI Z3 digital camera operated from a Matrice 100 quadcopter drone (Da-Jiang Innovations Science and Technology Co., Shenzhen, China).

4 Landsat systems for detection of pests at macro-scale detection ranges

Landsat satellite technology has been in operation since 1984, providing the capability for long-term analyses of changes in forest coverage over time (e.g. Senf et al., 2017). Multiple image processing algorithms have been developed to make the data for such analyses easily accessible to researchers (Kennedy et al., 2018). Because crop insect pests are not large enough to be directly detectable at Landsat-scale detection ranges, this technology is not yet widely used by farmers and researchers, although there is potential that future generations of Landsat satellite cameras with higher resolution may enable development of such capabilities.

5 Sound- and vibration-sensors for pest detection

In cropland environments, the weak sounds and vibrations produced by insects in air, soil, or plant tissues are embedded in soundscapes (Pijanowski et al., 2011) and vibroscapes (Šturm et al., 2022) containing varying levels of human-produced background noise, often more audible than the pests targeted for detection. Insects that produce sufficiently audible airborne sounds are easily recorded by currently available, portable passive acoustic monitoring (PAM) systems (Sugai et al., 2020). Acoustic signal analyses and machine learning toolkits have been developed to process the recorded signals, filter out background noise, and identify important features by which different sound-producing animals and insects can be compared. Ulloa et al. (2021) developed a toolkit that can scan large audio datasets and find regions of interest containing specific features that are user-programmable. Wu et al. (2022) developed a kit that contains features and sounds collected from multiple PAM databases to which the user can compare their own acoustic signals. Roch et al. (2021) reviewed supervised and unsupervised forms of machine learning that are most widely used to identify features of relevance to bioacoustics, oceanography, and music.

When targeted insect pests move and feed in soil, plant tissue, or other opaque substrates, the effects of airborne background noise can be reduced by connecting customized piezoelectric attachments or waveguides directly to the substrates (Mankin et al., 2011; Rigakis et al., 2021a). A similar effect occurs when pest-generated vibrations inside a tree are transferred onto a substrate such as an optical fiber that is wrapped around the tree trunk (Ashry et al., 2020). Vibrations produced by insect larvae as they move and feed inside a tree intermittently alter the effective refractive index of fiber wrapped around the tree and, when optical pulses are transmitted at one end of the fiber, the Rayleigh backscattered traces of the pulses show intermittent intensity fluctuations (speckles) that can be monitored and interpreted. Also, the behavior of sapsucking hemipteran insects can be detected by means of electrical penetration graphs, which can be used to guide the development of treatments that reduce feeding (Maluta et al., 2022) or identify mechanisms of plant resistance (Willet et al., 2016; Mercer et al., 2021).

Air- and substrate-borne signals collected at both meso- and micro-scale ranges typically are processed further to reduce background noise (Mankin et al., 2021). As with camera-produced images, machine learning or similar automated analysis tools (Romano et al., 2013; Jordan and Mitchell, 2015; Phung et al., 2017; Dong et al., 2018; Rathore et al., 2019; Bianco et al., 2019; Roch et al., 2021) can be applied to identify and compare salient features of the collected signals, including bursts of impulses from sliding, tapping, and snapping behaviors that distinguish between pest and nonpest insect larvae and also discard background noise (Mankin et al., 2008a,b). The behaviors of adult hemipteran pests that transmit vibrational signals along stems or tree branches can be monitored using vibration sensors assisted by traditional and machine-learning-based signal processing methods (Mankin et al., 2020b). In addition, the capability to disrupt mating communications has been demonstrated in multiple insect species that utilize vibrational signals during mating (Lujo et al., 2016; Zaffaroni Caorsi et al., 2021). The use of sensors that detect airborne or vibrational signals has been enhanced by the concomitant development of inexpensive amplifiers and user-friendly computer interfaces (Mankin et al., 2009a,b, 2010; Potamitis et al., 2009 Potamitis, 2013; Potamitis and Rigakis, 2014).

The instrument used most frequently to record insect vibrational signals in field environments before 2020, the AED-2010 (AEC, Inc. Fair Oaks, CA, USA), ceased production in 2019. Current replacements include Tree Vibes (Insectronics, Crete, Greece), used for detection of insect pests in trees (Rigakis et al., 2021a; Karar et al., 2022) and stored products (Mankin et al., 2021), and the Postharvest Insect Detection System (Custom Engineered Solutions, W Hempstead, NY, USA), used for stored product insect detection Mankin et al. (2020a). Other potential pest insect detection devices for which no scientific reports are yet available are listed in Table 4. Background information about the pseudo-acoustic sensor and signal processing technology used for the FarmSense device is provided in the studies by Batista et al. (2010), Katzanek (2020), and Mercer et al. (2021).

Table 4 Commercially available acoustic-, pseudo-acoustic-, and camera-based pest insect detection systems for field use

Sensor type	Company Name and Location	Website
Accelerometer	Smart Palm, Prince Sultan Univ., Riyadh, Saudi Arabia	https://doi.org/10.3390/agronomy10070987
Acoustic (unknown)	IoTree Pest Detection, Rockville, MD, USA	https://www.agrint.net
Cell phone	Palmear Al Karama, Jordan	https://www.palmear.ai/
Cell phone	Permia Sensor, London, UK	https://permiasensing.com/
Pseudo-acoustic	FarmSense flying insect Detection, Riverside, CA, USA	https://farmsense.io
Unknown	iPalm Digital Platform, Russell IPM, Flintshire, UK	https://russell-iot.com/portfolio/ipalm/
Camera	Trapview, EFOS, Slovenia	https://www.trapview.com/v2/en/
Camera	iSCOUT, Pessi Instruments, Weiz, Austria	https://metos.at/iscout/
Camera	SightTrap, Insects Limited, Westfield, IN, USA	https://www.insectslimited.com/sighttrap
Camera	Spensa Technologies, Burnsville, MN, USA	https://dtn2.flywheelsites.com
Camera	SPOTTA, Cambridge, UK, and Los Angeles, CA, USA	https://www.spotta.com

It should be noted that several of the systems described earlier, including the Smart Palm system for the detection of *Rhynchophorus ferrugineus* (Olivier; Coleoptera: Dryophthoridae) larval vibrations in trees (Koubaa et al., 2020), also employ sensors that detect temperature, humidity, and pH in addition to vibration and sound. Such sensors provide additional, cost-effective information to farmers and pest managers, which can enable 'smart farming' (De Alwis et al., 2022) technologies to play a broader role in agriculture in the future.

6 Case studies: augmenting traditional pest detection and biological control with nano-scale- and micro-scale-sensor technologies

Combinations of traditional pest management methods and complementary technologies can provide broadscale sensing tools which improve understanding of pest behavior over macro- to nano-scale detection ranges (Table 2). An example is the macro-scale modeling of yearly migrations of multiple strains of *Spodoptera frugiperda* (J. E. Smith) (Lepidoptera: Noctuidae) within North America. Early generations are first seen in overwintering areas in southern Texas and Florida. In late winter, first and later generations follow warming temperatures and prevailing winds through spring and summer, causing crop damage in locations as far north as Canada (Westbrook et al., 2019). Two strains of *S. frugiperda* have been identified, one found primarily on grasses, including rice, and one primarily on corn (Nagoshi et al., 2007b). Adults captured by pheromone traps were tested by genetic marker analysis to distinguish between rice and corn strains. The corn strains were subdivided further into four haplotype subgroups using cytochrome C oxidase subunit I markers and single nucleotide polymorphisms (Nagoshi et al., 2007a, 2017), sensing in the nano-scale detection range (Table 2). The combinations of such technologies in the study provided fine-grained information about the migration pathways of each strain for geostatistical dispersal models that Westbrook et al. (2019) developed to predict the magnitudes and times of pest dispersal. It should be noted also that plots of insect population distributions obtained by Spatial Analyses by Distance Indices and other geostatistical analyses can similarly provide important information for targeting crop pest infestations (Mankin et al., 2007).

Traditional biological control efforts also benefit from the complementary use of ERG and EAG electrophysiological tools, as well as three-dimensional printing of specially designed visual and pheromone traps to improve understanding of how insect pests employ visual and chemical cues to orient to their host crops. Combined behavioral and electrophysiological studies of a devastating citrus pest, *Diaphorini citri* (Hemiptera: Liviidae) (Allan et al., 2020), have enabled a better understanding of *D. citri* attraction to differently colored sticky traps, for example. It was determined that traps coated with magnesium oxide and/or barium sulfate were more attractive due to the attraction of *D. citri* to ultraviolet light, which is strongly reflected by such coatings (George et al., 2020). *Diaphorina citri* orientation to light was affected by both wavelength and polarization (Paris et al., 2017). George et al. (2016) discovered also that two degradation products of citrus tree VOCs, formic and acetic acid, play a role in *D. citri* attraction to host trees. Similarly, using EAG methods, Yang et al. (2019) identified four highly active VOCs produced by soybean (*Glycine max* (L) Merrill. and kudzu (*Pueratia montana* (Lour.) Merr. var. Lobata (Willd.) plants that were strongly attractive to the invasive Kudzu bug, *Megacopta cribraria* (Fabricius) (Hemiptera: Platispidae) in olfactometer bioassays. Additional studies of insect pests physiological and behavioral responses may lead to further improvements in trapping systems.

Three-dimensional-printed traps have been developed to improve the detection of the bacterium causing huanglongbing (citrus greening disease, HLB) that causes the death of citrus trees (Singerman and Rogers, 2020). The bacterium is vectored by an invasive citrus pest, *D. citri* Kuyayama (Hemiptera: Liviidae). *Diaphorina citri* were trapped in laboratory, greenhouse, and field environments (Snyder et al., 2022) by three-dimensional traps that contain a liquid preservative which does not quickly degrade the disease pathogen. Such traps not only detect the presence of *D. citri* in citrus groves but also determine whether they are vectors of the bacterium that produces HLB. Management of citrus in areas where HLB is not yet endemic is strongly dependent on how rapidly the disease is spread. The three-dimensional traps can be printed and deployed rapidly to monitor quickly the spread of HLB in a small area and remove infected trees.

For silverleaf whitefly, *Bemisia tabaci* (Biotype B) (Gennadius) (Hemiptera: Aleyrodidae) and other pests that have developed increased resistance to insect growth regulators and neonicotinoids (Dennehy et al., 2010; Perring et al., 2018), there is a need to maintain the presence of predators, parasitoids, and other ecosystem services that would normally reduce pest populations (Bradshaw et al., 2021). Areas with high insecticide usage would benefit from improved habitat manipulation and other biological control techniques to reduce economic losses (Naranjo, 2001). ‘Push-pull’ strategies have been tested in different ecological contexts, some of which yielded successful results (Oji and Mohamed, 2005; Li et al., 2014). Habitat manipulation and ecosystem engineering (Zhong et al., 2022) that provide or eliminate visual and olfactory cues could facilitate improvements in ‘push-pull’ effectiveness (Potting et al., 2005), and improved VOC technology and behavioral bioassays have fostered such progress. Recently, mustard plants and oils were found to repel *B. tabaci* (Legaspi et al., 2016) and thus could be used as part of a ‘push-pull’ strategy welcomed by organic crops growers (Allan 2018; Khan et al., 2014a,b; Tyler-Julian et al., 2018). Plant surface repellency combined with VOC repellency has been successful against *B. tabaci* in studies applying limonene-scented kaolin to tomato crops (Johnston et al., 2022). Natural enemy refuges have been of continued interest for biological control in studies such as those by Corbett and Rosenheim (1996), Meagher et al. (2019), Juliano and Gratton (2020), and Clem and Harmon-Threatt (2021). Increased technological capability to monitor populations of natural enemies in refuges can benefit refuge maintenance efforts. Mechanical barriers such as exclusion screening to keep crop plants free of specific insect pests have been cost-effective where a few pests can vector diseases over large areas (Ebert et al., 2020) and may be used increasingly in areas where the plants would benefit from reductions in solar radiation or increases in relative humidity (Mahmood et al., 2018). Crops within such exclusion barriers benefit from traditional or complementary methods of detecting pest insects that may have evaded barriers to entry.

A recent focus in biological control is the development of a better understanding of the effects of host-associated differentiation (HAD) of pest strains or biotypes on their natural enemies (Thompson et al., 2022). A crop pest may experience HAD when it begins to mate preferentially on a particular host crop, recognizing highly specific tactile, olfactory, and taste cues of the host. Advances in knowledge of chemical cues that affect natural enemy foraging behavior have led to the recognition that, when crop pests evolve through HAD, their natural enemies may be affected in ways that cause them to exhibit HAD as well (Harrison et al., 2022). The adaptation process may be more rapid than previously thought, as recent studies have demonstrated that continuous adaptation to rapid environmental change occurs in *Drosophila melanogaster* Meigen (Diptera: Drosophilidae) (Rudman et al., 2022), which has a relatively short 10-day generation time. Better knowledge of HAD and the associated differences that occur in herbivore-induced plant volatiles (HIPVs) can help researchers select natural enemies that target the insect pest more precisely. Technological improvements in the detection, analysis, and manipulation of HIPVs thus are assisting the process of selecting natural enemies with greater capacity to reduce pest insect populations (Stelinski et al., 2019).

7 Conclusion

Physical energies and processes that can be used to detect pest insects in agricultural settings include electromagnetic energy (light, infrared, radar, etc.), sound and vibration energy, and biochemical reactions and syntheses. All of these are used singly and in combination to complement traditional information from human sensory modalities of vision, audition, touch and vibration, olfaction, and taste. Examples of modern sensor technology are described that enable pest insect detection over a greater range (scale) of distances, often with greater precision than human sensory systems provide. The use of electronic sensors also enables real-time data collection, storage, and analyses by computer systems. Machine learning and deep learning software algorithms have been developed that enable the identification and use of important features of the detected signals to precisely identify pests and distinguish pest species from each other. A goal is to target applications of control treatments to locations where the pest insects are present, thereby reducing treatment costs and reducing harm to nontarget organisms. The costs of purchasing and using the new technology in agricultural environments are decreasing, especially when sensors that detect temperature, humidity, pH, and other environmental conditions important to crops are included together in systems that relay information to farmers and managers. In addition, enhanced knowledge of pest distributions obtained from the use of these sensors enables more effective use of 'push-pull' technologies and other biological control methods.

8 Future trends in research

Deep learning is not the 'Amulet of Yendor,' but much of the upcoming effort to distinguish among insect species by use of data stored as images, sounds, and/or vibrations is likely to apply deep learning or similar methods to assist in crop insect pest detection unless they are quickly supplanted by even more precise methods. If such methods are developed, they are likely to incorporate signal features that entomologists have already identified to be singularly important for pest identification. Exclusion screening or screenhouses may become more important in regions that have become hotter and drier due to climate change, especially if the excluded insects are important pests or vectors of plant disease and have become resistant to pesticides. Out of sight out of mind, soil invertebrates may slowly gain in interest to pest managers, as their significant roles in crop ecosystems become more apparent (Johnson et al., 2007; Inyang et al., 2019; Veen et al., 2019; Helmberger et al., 2022 Mankin, 2022).

Finally, the arms race between crop insect pest resistance and pesticide manufacturer ingenuity is likely to continue, as noted by Sparks et al. (2019), complicated by the effects of climate change that may benefit the pests while harming crops and increasing farmer costs of controlling and monitoring pests with higher metabolic rates (Deutsch et al., 2018; Skendžić et al., 2021). A standoff is the most likely result, although an improved understanding of the bioactivity of commercially developed insecticides and natural products may tip the balance in favor of the farmer.

Table 5 Locations of crop pest detection research centers by region

Region	Institution	References
Europe		
Slovenia	Univ. Ljubljana, Slovenia	Virant-Doberlet et al. (2019)
Greece	Hellenic Mediterranean Univ., Chania, Crete; Univ. West Attica, Athens, Greece	Potamitis et al. (2019); Rigakis et al. (2021b)
Italy	Univ. Trento, Italy	Avosani et al. (2021)
Switzerland	ETH, Zurich	Maeder et al. (2022)
France	CNRS, Paris	Šturm et al. (2022)
Germany, UK	Hoch. Geisenheim Univ. Geisenheim; Univ. York, York; Oxford Univ., Oxford	Görres and Chesmore (2019); Mortimer (2019)
North America		
(Western to	UCLA, Los Angeles, CA	Montgomery et al. (2021)
Eastern centers)	USDA, Parlier, CA; Adair, OK	Higbee and Burks (2021)
	UC Riverside, CA, Univ. BC, Vancouver, Canada, Northern Ariz. Univ., Flagstaff, AZ, Univ.; Canterbury, NZ	Liao et al. (2022)Bedoya et al. (2021)
	U. Missouri, Columbia, MO	Kollasch et al. (2020)
	Univ. Toronto, Toronto, ON; NAFRO, Tsukuba, Japan	Nakano and Mason (2018)
	Carleton, Univ., Ottawa, ON	Low et al. (2021)
	USDA, Gainesville, FL; FAMU, Tallahassee, FL	Inyang et al. (2019)
	Argonne Nat. Lab., Binghamton, NY; Cornell Univ., Ithaca, NY	Zhou et al. (2022)
	Stevens Inst., Hoboken, NY	Sutin et al. (2019)
South America	EMBRAPA, Sao Paulo, Brazil	Laumann et al. (2018)
Asia		
India	Janta Vedic College, Baraut, India	Banga et al. (2020)
Sri Lanka	Rinzen Lab., Rattanapitya, Sri Lanka	Siriwardena et al. (2010)
Australia	Macquarie Univ., Sydney, AU; La Trobe, Univ., Melbourne, AU	Wignall and Taylor (2011); Lubanga et al. (2021)
New Zealand	Massey Univ., Auckland, NZ	Wignall and Herberstein (2022)
Japan	NAFRO, Hiroshima; Kyoto Univ. Kyoto	Kawakita and Ichikawa (2019)
China	Shaanxi Normal Univ. Xi'an; Chinese Acad. Sci, Beijing	Sun et al. (2018); Wu et al. (2022)

While looking forward, it is worthwhile to think back 50 years to the partially fulfilled promise of the Green Revolution (Vandervoet, 2022). One can only hope that scientists, engineers, and governments also can develop

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improved methods to reverse the ongoing decline of ecosystem services including clean air, potable water, and high-quality soil (Bradshaw et al., 2021) as human populations and consumption increase and the frequencies of occurrence of hotspots of acute food insecurity continue to escalate (WFP and FAO, 2022).

9 Where to look for further information

Centers where arthropod acoustic or vibrational studies of practical interest are conducted frequently include those listed in Table 5, arranged geographically along with references to relevant publications.

Recently, many studies have focused on the development of computer methods to identify digital images of insect pests due to the decreased costs of collecting images. Such studies are discussed in other chapters of this book.

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