BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Advances in insect pest and disease monitoring and forecasting in horticulture

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1 Introduction

1.1 Knowledge domains of monitoring and forecasting research

Integrated pest management (IPM) is repeatedly characterized as a knowledge-intensive approach for plant protection. Thresholds for interventions and sampling for pest occurrence, the results of which inform whether a threshold has been reached, form the foundation and central organizing principles of all IPM activities (Castle and Naranjo, 2009). Information collected from the crop on occurrence or densities of pest(s) must be appraised in respect to the status of the crop system. The system's status concerns, among other things, crop phenology and its associated sensitivity to pests compared with pest density and prevailing and forecast weather conditions that will influence pest development.

Based on the information collected and its appraisal, a decision needs to be made: whether or not to intervene and how to intervene? Decisions, in turn, are appraised through a socioeconomic filter: crop value, cost of intervention, the farmer's level of risk taking and ecological, economic and social considerations of the sustainability of crop production. Farming objectives, the farmer's and society's values and attitudes and the farm's economic situation, all modulate

http://dx.doi.org/10.19103/AS.2021.0095.05

Chapter taken from: Collier, R. (ed.), *Improving integrated pest management in horticulture*,
Burleigh Dodds Science Publishing, Cambridge, UK, 2022, (ISBN: 978 1 78676 753 0; www.bdspublishing.com)

the selection of tools needed for information collecting and appraisal, as well as the decisions made based on that information.

To develop efficient tools for the implementation of monitoring and forecasting in practice, we need scientific research and knowledge and/or technological innovations from at least four different domains (Fig. 1): (1) biology and ecology of the pest and pest identity; (2) pest detection to estimate the pest's density or proportion of infested sampling units; (3) evaluation of the data on pest densities for decision-making with the help of pre-established reference thresholds that bring bioeconomics into the picture; and (4) forecasting of anticipated pest developments within and/or between the growing seasons. In the case of invasive pests, detecting and forecasting concern also their dispersal and establishment in new geographical regions. Forecasting can in some cases replace direct pest detection, but more often these two domains complement each other: forecasting results inform the grower about when and where to start monitoring.

At this point one thing must be made clear. Sampling and monitoring are not, strictly speaking, the same thing. Sampling is a one-time process of acquiring necessary information on the real-time pest status of a crop by using a sampling protocol (plan). Pests can be sampled for example by directly counting them on crop plants, by vacuuming, sweeping or beating to remove pests from plants for counting, or by destructive sampling by removing whole

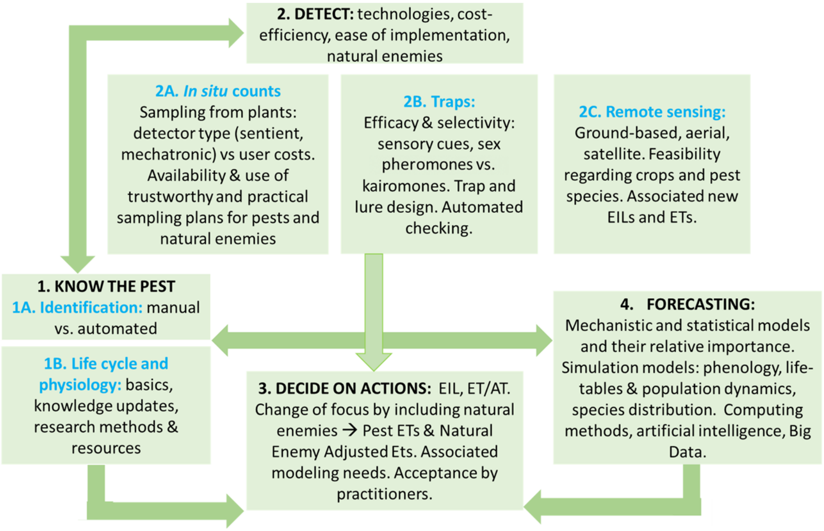


Figure 1 Four knowledge domains needed to develop tools for monitoring and forecasting insect pests. Identified challenges are listed after the domain name. EIL, economic injury level; ET, economic (damage) threshold; AT, action threshold. The arrows indicate the dependence of the domains on each other (see text for details).

plants or plant parts for counting pests on them. Flying pests can be sampled using different types of traps: suction traps or traps that attract pests with colour, light or odour sources and that are equipped with a sticky surface or a vessel filled with liquid where insects are trapped. Depending on the sampling method, pest counts are either absolute or relative. Monitoring denotes the use of a sampling plan sequentially in time to monitor the change in the density of the target pest population – such repeated sampling can be called cascaded sampling. (Binns et al., 2000). Pest forecasting concerns the predicted occurrence and/or activity of biotic agent(s) that could cause economic damage to a crop, usually in the near future. Forecasting is customarily based on the knowledge concerning the impact of weather or climate on pest biology (Olatinwo and Hoogenboom, 2014) in order to predict the timing of pest attack or pest population development (Finch et al., 1996; Phelps et al., 1993)

The arrows in Fig. 1 depict how the four knowledge and technology domains associated with pest monitoring and forecasting interact with each other. Knowing the pest's biology, ecology and behaviour and being able to identify it are necessary for developing reliable detection methods and decision-making tools. Economic injury levels (EILs) and economic damage thresholds (ET) cannot be developed without understanding how the pest utilizes its plant resources in comparison with farmers' goals regarding those resources. Each method of detecting the pest requires associated knowledge on the relationship between pest counts and economic damage to the plant population. The nature of the economic damage imposes requirements on the nature of detection methods (e.g. how early the pest must be detected so as to be able to manage it with the existing tools for intervention). Pest identification issues are often intricately related to the detection method, since the latter influences the condition in which the pest is available for identification and how many other species interfere with the identification task.

The biological, ecological, phenological and sometimes even genetic fundamentals of the pest must be known so as to be able to develop forecasting models that accurately predict pest emergence and population dynamics. The forecast results, in turn, contribute to or wholly enable decision-making concerning interventions and their timing. Simulation models may reveal important new aspects of the pest's behavior, biology, ecology and/or bioeconomics that would be very laborious and resource-demanding to study empirically.

1.2 Mini reviews on 12 pest species to collect information on bottlenecks and challenges in the knowledge domains

For this chapter, the way of identifying the bottlenecks and challenges concerning monitoring and forecasting was as follows: a total of 12 key insect or mite pests of seven important fruit, berry and vegetable crops – apple, strawberry, cruciferous vegetables, onion, tomato + cucumber and carrot – were chosen for mini reviews on their status of monitoring and forecasting (Table 1). These pests included species that directly damage the end product and those that damage only non-saleable parts of the crop. Whiteflies were chosen as pests for a closer case study, as the author is most familiar with their biology and management. Through the 12 mini reviews, it was possible to obtain a picture of the status of research and implementation of monitoring and forecasting in horticultural crops that form important parts of the human diets all over the world, with emphasis on the boreal, temperate and Mediterranean climate zones.

Literature searches were made for the chosen pests on the status of the methods for their practical identification and detection and sampling programs, and also decision-making tools and forecasting of phenological development or population dynamics. The status of knowledge on the biology, ecology, etc., of the pests was reviewed only to the extent that was necessary to understand why there were bottlenecks in the above knowledge domains. Based on reviewing the status of monitoring and forecasting for the chosen pest species, the issues depicted in Fig. 1 were identified as crucial ones for the development of monitoring and forecasting systems for pests of horticultural crops. Other issues could have emerged had the sample of crops and pest species been larger.

1.3 Overview of bottlenecks and challenges in pest monitoring and forecasting

Sampling and detection require time, labour, and identification skills (Binns et al., 2000). There is a tendency for farmers and scouts to try to minimize the time needed for sampling based on in situ counts and checking traps (Agnello et al., 1994; Hamilton et al., 2004; Rincon et al., 2020). At the same time, farmers' tendency for risk aversion is influenced by the 'uncertainty associated with pest sampling and forecast information', EILs and ETs (Gent et al., 2011; Milner-Gulland and Shea, 2017). Uncertainties are caused by for example yearly trends in commodity values (Damos, 2014) and abiotic and biotic conditions that influence pests and natural enemies, efficacy of pesticides, yield levels and losses and the correlation between pest densities and economic losses (Johnson et al., 1992; te Beest et al., 2013). If exact information on these variables is not available at the time of sampling and forecasting pest population development, the inclusion of their variance, by way of a probability distribution, in calculations of ETs can be used, instead of explicitly known values. This results in probabilistic EILs (Peterson and Hunt, 2003), which instead of taking mean values for the parameters C, V, I and D in the EIL function (see Fig. 2), use the whole range of probabilities for values of these variables. For

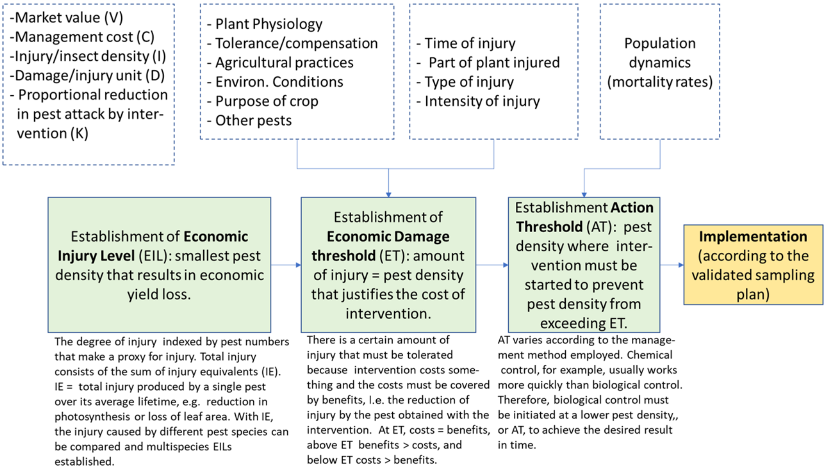
Table 1 Pests of five horticultural crops chosen for mini reviews that were used as the basis of identifying bottlenecks and stalled research concerning the pest species' monitoring and forecasting. EILs and ETs are available for all these pest species, either based on in situ counts or counts from traps, or both

Crop	Pests causing direct damage to the end product	Pests causing indirect damage to the crop
Apple	1. *Cydia pomonella* (codling moth)[1,2,5,6] 2. *Argyresthia conjugella* (apple fruit moth)[1,2,4,5,6]	3. *Panonychus ulmi* (European red mite)[4,5,6]
Strawberry	4. *Drosophila suzukii* (spotted wing drosophila) [2,3,4,5] 5. *Anthonomus rubi* (strawberry weevil)[2,4,5]	6. *Phytonemus pallidus* (strawberry mite)[4,5,6]
Crucifeours vegetables	7. *Delia radicum* (cabbage root fly)[2,3,4,5,6] 8. *Plutella xylostella* (diamondback moth) (direct pest in some crops)[1,4,5,6]	10. *P. xylostella* (indirect pest in some crops)[1,4,5,6]
Onions	11. *Delia antiqua* (onion fly) [3,5,6]	
Carrot	12. *Psila/Chamaepsila rosae* (carrot fly)[3,6]	
Tomato and cucumber (greenhouse)		13. Whiteflies (*Trialeurodes vaporariorum* greenhouse whitefly, *Bemisia tabaci* sweetpotato whitefly)[3,4,5,6]

[1] Sex pheromone available for attracting males to traps; [2]Other semiochemicals available or under product development for attracting both males and females, either alone or in combination of sex pheromones; [3]Visual traps commonly used for monitoring; [4]Sampling plans available for in situ counts from plants/soil for estimating abundance; [5]EILs and/or ETs available for decision-making at least in some crops; [6]Degree day or phenology models available for predicting emergence, flight peaks and/or population dynamics/trajectories, at least in some crops/regions. References will be given later in the text.

growers this means, for example, that they can choose from different levels of EILs depending on their risk aversion level. A risk-averse grower could choose a lower EIL that occurs only 25% of the time, due to uncertainties associated with the above variables (Higley and Peterson, 2009). Probabilistic EILs and ETs are rare, although they would address the very problem of uncertainty of EILs and ETs and farmers' risk aversion and its consequences for decision-making. Uncertainty of information tends to result in treating the crop even when there would be no need to treat it (Gent et al., 2011; McRoberts et al., 2011) or taking control actions before pest forecasts recommend taking action (Evans et al., 2017; Möhring et al., 2020). For farmers, the value of information about yield prospects and not suffering yield losses tends to be higher than that about pest density (Pannell, 1994). Farmers' risk aversion and uncertainty of information concerning pest numbers must be taken into account when developing and implementing sampling/monitoring and forecasting tools (Evans et al., 2017).

Pest insect identification is seldom a problem with traps based on female sex pheromones that only attract males to the traps (Witzgall et al., 2010).



The degree of injury indexed by pest numbers that make a proxy for injury. Total injury consists of the sum of injury equivalents (IE). IE = total injury produced by a single pest over its average lifetime, e.g. reduction in photosynthesis or loss of leaf area. With IE, the injury caused by different pest species can be compared and multispecies EILs established.

There is a certain amount of injury that must be tolerated because intervention costs something and the costs must be covered by benefits, I.e. the reduction of injury by the pest obtained with the intervention. At ET, costs = benefits, above ET benefits > costs, and below ET costs > benefits.

AT varies according to the management method employed. Chemical control, for example, usually works more quickly than biological control. Therefore, biological control must be initiated at a lower pest density,, or AT, to achieve the desired result in time.

Figure 2 Phases of developing economic injury levels and economic thresholds for decision-making in pest management. Based on Radcliffe et al. (2009) and Higley and Pedigo (1996).

Sex pheromones are available for all three Lepidopteran pests mentioned in Table 1, but not all pest species use sex pheromones for attracting mates. The performance of sex pheromones is not always sufficient or it is too variable, as with *Plutella xylostella* (Evenden and Gries, 2010); their use could benefit from combining them with additional semiochemicals (Dai et al., 2008; Li et al., 2012). The high selectivity of sex pheromones can be problematic, too. With only male captures, it is difficult to make exact projections of crop damage, as it is ultimately the females that are responsible for the damage. The correlation between captured male counts and crop damage is not necessarily very good, thus the precision of trap catches in predicting damage needs improving for some pests (Adams, 2017). Therefore, it is desirable to also attract females to traps but without attracting too many non-targets.

Usually only a few traps based on sex pheromones are used per orchard or field, but even so, checking them still takes time and effort and requires walking to the traps to check them. This issue is addressed nowadays with traps equipped with cameras to enable automated checking of traps and even automated identification of trapped insects (see Section 2.1). Furthermore, the frequency of false negatives and overestimated positives (e.g. codling moth trapping) can be high with single, widely spaced traps, adding to the uncertainty of trapping results. (Adams, 2017). Males entering traps baited with sex pheromones do not always indicate damage potential, even if thresholds are exceeded. Knowing the pest's biology and ecology is important. The apple fruit moth (*Argyresthia conjugella*) lays eggs in apples only when there are insufficient rowan berries for the whole female population (Kobro et al., 2003; Tuovinen, 1987). It is therefore important to know not only the number of males coming to traps but also the number of rowan berries available for egg-laying with respect to the estimated size of the female population. Methods exist for this and should be combined with the use of traps (Edland, 1974; Tuovinen, 1987).

Food baits or plant-derived kairomones alone may not be as effective at attracting insects as sex pheromones (Landolt et al., 2007), and it can be difficult to find the right kinds of combinations of substances that would function equally well in all plant species backgrounds (Knudsen et al., 2017). The chemical ecology of herbivores has been a thriving domain of science only since the 1990s. There are still surprises to be revealed about how herbivores interact with their biotic environment, as exemplified by the recent advances in the chemical ecology of *Drosophila suzukii*.

Low sampling and trapping selectivity is an important bottleneck for reliable estimation of pest densities and can seriously hinder the uptake of sampling plans by practitioners. New, more efficient solutions for detecting and trapping pests lead to the need for developing new EILs, ETs/action thresholds (AT). The ET is theoretically dependent on the EIL (Pedigo et al., 1986), but it is very common for an ET to be established in isolation, as a practical action level arrived at through experience or direct field testing. This is because substantial research is required to derive an EIL (Fig. 2), so revisions of ETs are often based on experimentation (Hamilton et al., 2009a). Such experimental revisions may be possible for combinations of different pests that occur in the crop simultaneously, but once natural enemies are incorporated into EILs and ETs, mere empirical research can get very complicated. Modelling is needed to understand how natural enemies influence pest density in different scenarios of pest population dynamics.

Determination of EILs for crop plants had its peak period in the 1980s, and since then this research activity has been declining (Castle and Naranjo, 2009). The context for use of EILs and ETs is gradually changing due to removal of rapidly acting pesticides from the market for reasons of human and environmental health (Collier et al., 2020). Thus, EILs and ETs may gradually lose their importance as mere thresholds for curative intervention with pesticides. Binns et al. (2000) consider EIL too narrow a concept: in its current form, it does not take into account that a grower may have other values than profit that guide her/his decision-making.

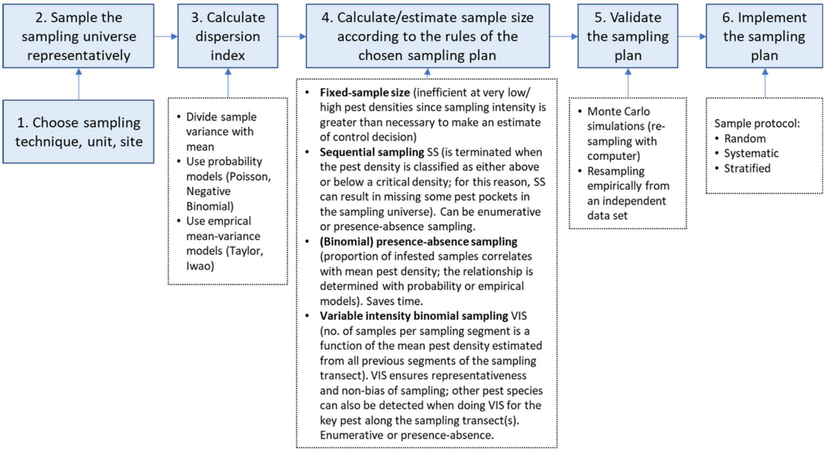
> With increased reliance on biological control, cultural management and host plant resistance, pest control decision rules, and especially monitoring, will become even more important. Because it is often difficult to quantify the abundance of natural enemies, let alone predict their impact, monitoring [i.e. repeated sampling on time, particularly when there are multiple pest generations per growing season] is a useful tool for assessing the effectiveness of biological control.
>
> *(Binns et al., 1996)*

The incorporation of natural enemies in ETs brings along several challenges related to the uncertainty of factors that influence the EIL and ET and methods of threshold development. Growers in developed countries in particular tend to focus on economic returns and risk-averse management tactics, as explained above. Therefore, they may consider reliance on biological control too risky (Giles et al., 2017 and references therein) unless they have access to reliable, standardized impact data reports on biological control efficacy that are comparable across cropping systems, just as pesticide efficacy tests are reported (Giles et al., 2017). According to Macfadyen et al. (2015), when assessing the impact of natural enemies, the timing and consistency of mortality caused by natural enemies between seasons can be more important than the magnitude of mortality attributed to them. Impact assessments must be tailored according to the needs of farmers and the specific pest problems they face so that natural enemies can be incorporated as an integral part of decision-making, particularly upon reliance on conservation biological control (Macfadyen et al., 2015). But, as these authors state, studies on tangible quantified impacts of natural enemies associated with ETs are still scarce. Macfadyen et al. (2015) list the challenges and key research questions associated with assessing the impact of natural enemies and describe methods to assess the impacts. Whether obtaining such impact data is possible at all, and under what circumstances such data can be relied upon, is a matter of investing in empirical research and modelling of the impact of natural enemies, communicating the results and understanding farmers' perceptions and approaches to IPM when developing EILs and ETs. EILs and ETs incorporating natural enemies will require more thorough information on the role and biology of natural enemies in different crops as well as how to sample for them (Giles et al., 2017) (Fig. 3). This calls upon new biological, ecological and behavioural research on natural enemies and the factors that influence their performance. Modelling the interaction of pests and natural enemies also becomes more important than before in order to be able to incorporate their impact into EILs and ETs. To calculate economic impacts of natural enemies, modelling can be used as a starting point to create hypotheses that can be tested empirically in subsequent phases of research. One example is modelling the quantitative effects of entomopathogenic fungi in reducing yield losses of cereals by aphids (Saussure, 2019).

The development and use of new sampling protocols must be included in the skill repertoire of crop protection researchers, consultants and growers, and that also involves skills to use models for validation. Sampling methods for natural enemies must be developed and their robustness compared and established to satisfy the requirements of trustworthiness of sampling (Table 2). In this new situation, ensuring the practicality of sampling can become an issue, as it is challenging even now. The interaction between theory and practice will gain a heightened importance.

Validation of sampling plans that include natural enemies is even more important than validating sampling plans for pests alone, but Castle and Naranjo (2009) stated that validation of sampling plans is often not done despite the fact that methods have been available since the 1990s (Hamilton et al., 2009b; Hull and Beers, 1990; Naranjo and Hutchison, 1997). In 2009, roughly half of the ETs developed were not accompanied by a corresponding sampling plan for their effective implementation (Castle and Naranjo, 2009). This is unfortunate because validation is particularly important for sampling plans developed for applying a decision rule involving ETs, the corner stones of decision-making in IPM (Castle and Naranjo, 2009).

Success of insect pest management actions is largely determined by the efficacy of the management action, the appropriate life stage of the pest targeted and the appropriate timing of the intervention (Tonnang et al., 2017). Forecasting is undertaken to predict the timing of crucial events in pest lifecycles so that management actions can be applied when they are likely to be most effective (Collier et al., 2020). Forecasting is based on models, that is, representations of the construction and working of systems of interest. A model must be both realistic and simple. Two general types of modelling approaches are commonly used for pest forecasting in IPM: mechanistic and statistical. Mechanistic models can be theoretical (analytical), or they can be simulation models of a given specific system. Simulation models are meant for experimenting on how the output changes when input parameters and



- Divide sample variance with mean
- Use probability models (Poisson, Negative Binomial)
- Use emprical mean-variance models (Taylor, Iwao)

- **Fixed-sample size** (inefficient at very low/ high pest densities since sampling intensity is greater than necessary to make an estimate of control decision)
- **Sequential sampling** SS (is terminated when the pest density is classified as either above or below a critical density; for this reason, SS can result in missing some pest pockets in the sampling universe). Can be enumerative or presence-absence sampling.
- **(Binomial) presence-absence sampling** (proportion of infested samples correlates with mean pest density; the relationship is determined with probability or empirical models). Saves time.
- **Variable intensity binomial sampling** VIS (no. of samples per sampling segment is a function of the mean pest density estimated from all previous segments of the sampling transect). VIS ensures representativeness and non-bias of sampling; other pest species can also be detected when doing VIS for the key pest along the sampling transect(s). Enumerative or presence-absence.

- Monte Carlo simulations (re-sampling with computer)
- Resampling empirically from an independent data set

Sample protocol:
- Random
- Systematic
- Stratified

Figure 3 Phases of development of a formal validated sampling plan, with short descriptions of the empirical and probability models needed to obtain the required parameters in different phases and perform sampling. Including natural enemies in the sampling will add a new layer or several new layers to the picture, depending on how many natural enemy species must be taken into account. Based on Binns et al. (2000); Hoy (1991); Naranjo (2008); Pedigo and Buntin (1993).

Table 2 Attributes of trustworthy sampling plans (Binns et al., 2000)

A trustworthy sampling plan has	What does it mean?
Good practicality	A simple enough procedure to appeal to users, not be misunderstood and must fit in with the agenda of the user regarding sampling time and the time it takes to collect the samples.
High representativeness	No unaccountable biases in the sampling protocol in selecting which instances of pest occurrence become sampled. This means several things (see bias)
Low bias	Bias is the difference between the expectation of an estimate and the true value. Bias is caused by many things, for example, by: (a) taking too few samples (can be a problem in sequential sampling plans if a minimum sample size is not given); (b) taking samples from just some parts of a field and leaving other parts unsampled; (c) selecting samples based on how easy it is to reach and process them; (d) selecting sample units on the basis of a characteristic which is correlated with the properties to be investigated by sampling; and (e) substituting omitted or rejected sample units by more readily observable units.
High reliability	No uncontrolled variables should influence the sampling protocol. They include the person collecting the data, weather, or possible diurnal behaviour of the pest (determines sampling time). Reliability and representativeness together ensure that the sample mean, m, is an unbiased estimate of the true pest density, μ.
Reasonable relevance	The estimate of pest abundance has a reasonable relationship to crop yield and loss.
Moderate to high precision depending on the goal and practicality of the sampling plan.	Refers to how close to its own expectation one single estimate is. Increases with increasing number of samples. A lower precision is often acceptable in sampling plans for decision-making in IPM. Moderate precision, is, however, required even then.
Good accuracy	A measure of how close an estimate is to what it is estimating. Can be estimated by the mean square error, mse (the greater the mse, the lower is the accuracy). Incorporates both bias and precision. Example: an estimate may have high precision, but low accuracy because of high bias.

configuration of input variables are changed in the system of interest. They should preferably involve stochasticity (i.e. at least one of the input or output variables is probabilistic) (Maria, 1997). In pest forecasting, the goal is to understand the role of different factors for the change in pest or natural enemy population dynamics (Prasad and Prabhakar, 2012).

The mechanistic approach is based on causality and tracks pest dynamics in a process model that simulates the development of the target organism and perhaps its host(s) and natural enemies. Mechanistic models are based on knowledge on how the input variables lead to the output(s), whereas statistical models give little or no insight into the specific processes leading to the output(s) (Baker et al., 2018). Mechanistic models enable the creation of new hypotheses concerning the functioning of the system of interest, whereas the purpose of statistical models is limited to prediction (Table 3). Statistical models are correlative. They range from simple regressions to much more complex models such as Bayesian models where probabilities represent all uncertainty contained in the input parameters and outputs, and finally to models based on artificial intelligence (AI) methods operating on very large data sets.

Mechanistic modelling involves two stages. First, the model is constructed and calibrated by using a subset of the available data. This is done with the help of simplified mathematical formulations of the assumed causal mechanism. Second, another subset of the data is used to validate and refine the model. Validating is needed to determine whether the range of possible input–output behaviours predicted by the model (the causality hypothesis) is consistent with experimental observations. After validation, the model can be used in applications where experiments are impossible or difficult to achieve (Baker et al., 2018). Magarey and Isard (2017) list problems and their causes and solutions associated with creating, parameterizing, validating and implementing mechanistic pest forecast models. Problems associated with the implementation phase can be rather challenging. Does the model represent stakeholder field observations? Are the model outputs useful to stakeholders, that is, do they give critical information for decision-making and is there time to act on the information in practice? Do stakeholders take the model into use at all due to time limitations or difficulties in understanding the model's outputs? These issues concern also the development of EILs and ETs.

Three subcategories of mechanistic models characterized by their input variables and output types are important for pest forecasting. First, phenology models are used to predict adult emergence time, peak adult flight and egg-laying activity, egg hatch or occurrence of damaging stages in order to optimize the timing of control measures. The measure of accumulated heat (degree days) provides a reference for the physiological age and development of organisms (Orlandini et al., 2017), but other weather factors such as rainfall or humidity can also be important, as shown for the emergence of the carrot fly, for example (Ovcharenko and Nikolaeva, 2020). Complete phenology models of insect and mite pests include mathematical functions for development time and rate, mortality, senescence, survival and reproduction of the species in question (Tonnang et al., 2017).

Phenology can be simulated in a deterministic or stochastic manner to yield the pest's life table parameters such as intrinsic rate of natural population increase (r_m), net reproduction rate (R0), finite rate of increase (ƛ), mean

Table 3 Features that differentiate mechanistic and statistical forecast models

Feature	Mechanistic forecast models	Statistical forecast models
Basis of relationship between inputs and outputs	Causality (Baker et al., 2018).	Correlation (Baker et al., 2018).
Basic tools	Mathematical equations describing the phenomenon of interest; associated assumptions to simplify the mathematical expressions that describe the relation between inputs and output (Maria, 1997).	Tools such as regression and AI algorithms that filter out irrelevant or redundant information to discover relevant co-occurrences and dependencies in the data (Baker et al., 2018).
Focus is on	(1) Understanding the mechanisms of pest development and infestation progression via mimicking real-life events; (2) generation of novel hypotheses for causal mechanisms through observations (Baker et al., 2018). Deductive approach.	Prediction via isolating relevant inputs from the dataset for a given output. Only little or no insight into the specific processes leading to the outputs. The predictive power of machine learning models increases with the number of unique cases that can be observed and used to train the predictor (Baker et al., 2018). Inductive approach.
Dataset size	Small data sets are OK (Baker et al., 2018).	Large data sets on historical or current events (Baker et al., 2018).
Extrapolation of prediction beyond the observed conditions	Yes (Baker et al., 2018).	No. Outputs are dependent on the specific input data and can only make predictions that relate to patterns within the data supplied (Baker et al., 2018).
Generation of new hypotheses	Good possibilities (Orlandini et al., 2017).	Less or no possibilities (Orlandini et al., 2017).

generation time (G) and the doubling time (t) (Tonnang et al., 2017). Another goal is to simulate the impacts of different pest scenarios on crop production when both yield losses and the effect of changing climate on organisms must be taken into consideration (Donatelli et al., 2017). For this purpose, crop and pest behaviour models must be coupled, which is not always easy (Donatelli et al., 2017). The eventual goal is, in fact, to be able to create complete simulation models that include biological, ecological, economic and social processes and their interactions, all of which together influence crop production and guide on the ways of managing crop systems (see Tonnang et al., 2017 and their reference to Walters et al., 2016). Tonnang et al. (2017) list a range of research questions that must be answered to achieve such an ambitious modelling goal. In accordance with such goals, bioeconomic models are expected to gain more importance as tools for creating EILs and ETs (Tonnang et al., 2017; Zhang and Swinton, 2012). Management of simulations and updation of decision support systems that use the simulations present large obstacles for implementing simulation models for pest forecasting (Orlandini et al., 2017).

Improvements of phenology models are still needed to make the outputs more precise and to improve region or site specificity of outputs, as shown for root-feeding insect pests such as the carrot fly and the cabbage root fly (Bažok et al., 2012; Biron et al., 2002; Collier et al., 2020; Dreves, 2006; Villeneuve and Latour, 2017) and the codling moth (Damos and Soulopoulou, 2019). Producing phenological forecasting models can be complicated by genetic and behavioural differences between different pest (or natural enemy) populations, as exemplified by the winter morphs of *D. suzukii* (Amarasekare and Shearer, 2013; Shearer et al., 2016) and late and early emerging forms of *Delia radicum*. In some regions, these two genotypes occur (Biron et al., 2002), whereas in other regions, all flies emerge synchronously (Johansen and Meadow, 2006). Migrating species such as *P. xylostella*, combined with climate warming, bring new challenges to the development of phenological and other forecasting models (Zalucki et al., 2017; Zalucki and Furlong, 2008; Zhu et al., 2018).

Most of the earlier models lack a stochastic function for variability in development times among individuals within a population, resulting in prediction errors (Orlandini et al, 2017). Furthermore, for insect species that exhibit seasonality, diapause or aestivation in their life cycles should be accommodated in the models. This can be done with Monte Carlo simulation modelling (Orlandini et al., 2017). Mechanistic phenological models are often built considering the developmental rate function only. The models can be enriched and their accuracy increased by including elements of demographic models in them, such as the age distribution of individuals which exit from the overwintering phase, the age- and temperature-dependent profile of the fecundity rate function and the consideration of a temperature-dependent mortality rate function, as exemplified for *Cydia pomonella* by Pasquali et al. (2019).

Second, life table and population models aim at representing and understanding different or selected factors such as, for the diamondback moth, host plants (Jaleel et al., 2019), temperature (Ngowi et al., 2017), specific natural enemies (Tonnang et al., 2010, 2009) or a combination of factors (Li et al., 2016) that influence population development and abundance. A drawback for forecasting the time and size of population peaks is gaps in the ecological databases such as short-range dispersal, overwintering behaviour, colonization patterns and age-specific mortality including inter- and intraspecific competition (Prasad and Prabhakar, 2012). Such obstacles may in some cases be bypassed using statistical models based on neural networks and large data sets (Tonnang et al., 2010). There is also some imbalance as to modelling the life cycle and population dynamics of different kinds of pests. For example, soil-borne diseases have not been modelled to the same extent as airborne diseases. Primary infection by active inoculum accumulated within the rhizosphere of host plants is the main target for model development (Orlandini et al., 2017).

One important input for pest modelling is pest observations. Sharing pest observations with other growers would allow everyone to see a more comprehensive picture of pest activity, but this is rarely done and tools for doing it are lacking (Orlandini et al., 2017).

Third, species distribution models (SDM) use a variety of algorithms to estimate relationships between species locations and environmental conditions and predict and map habitat suitability (Franklin, 2010). SDMs for pest forecasting can be used at two scales: predicting the establishment risk of exotic pests in new geographic areas of distribution (Franklin, 2010) and predicting where to target pest management actions in site-specific pest management within crop fields or orchards (Méndez-Vázquez et al., 2019). At both scales, SDM output is a risk map. At the larger, geographic scale, SDM make use of georeferenced presence data of species, digital maps of environmental variables and correlative algorithms such as Bioclim, Genetic Algorhitm for Rule Production, Maxent, or General Linear Models. For predicting insect distribution at geographic scales, Tonnang et al. (2017) list the advantages and disadvantages of commonly used inductive (statistical) and deductive (causal) approaches to using SDMs. Modelling alone is not always enough to predict how exotic species behave in new areas of distribution. Surprising results can be obtained with closer research as exemplified by the better than expected overwintering ability of *D. suzukii* in regions with cold winters (Thistlewood et al., 2018).

At the field scale, the classic precision agriculture techniques of zoning are enriched with one or more spatially explicit ecological layers (species' niches) that are created on the basis of a pest's within-field distributional patterns (Méndez-Vázquez et al., 2019). In addition to the model itself, it must be parameterized using high-resolution environmental data sampled with such precision agriculture tools as wireless sensor networks for plants, soil and air measurements, drones and remote sensing.

The relative status of mechanistic and statistical forecast models is changing with the advancement of statistical modelling approaches based on AI. With the growing number of observations and variables, the need for mechanistic models has been reduced and the predictive power of statistical models has increased. This is because a very large number of unique cases that can be observed and used to train the mechanism-free predictor essentially represent the whole reality that is covered in the input–output relationship. In the omics research, high-throughput methods of data collection produce very large data sets, but according to Baker et al. (2018), the research community remains focused on producing a plethora of potential mechanistic models that explain small pieces of a much bigger picture. The use of big data for forecasting in pest management research is not commonplace as yet, either, as concluded by, for example, Fenu and Malloci (2021), who studied the kinds of AI algorithms used for forecasting the onset of disease at a pre-symptomatic stage. One important obstacle of course is how to collect large amounts of data needed for big data analyses.

2 Addressing key issues and challenges of pest monitoring and forecasting

2.1 Automated identification of insects from traps and plants

2.1.1 Fixed camera-based systems

Automated identification with up to 100% identification success was developed for *C. pomonella* as early as 2011; this required a modified trap equipped with mobile phone cameras of different resolutions and a commercial acquisition and data transfer system using wireless technology to transfer the images for analysis (Guarnieri et al., 2011). Some other, smaller, insects came to the trap also, but they did not interfere with identification. The technical and operating characteristics used by Guarnieri et al. (2011) are nowadays regarded as being fairly basic. When a pest-selective sampling method provides 'clean' samples without non-target species and when the orientation of individuals in the traps allows complete feature extraction, automated identification is relatively easy based on images taken of trapped individuals and image analysis developed with machine learning or AI algorithms. With deep learning algorithms even the 'wrong' orientation of insects in traps, background clutter and interference from uneven illumination in the images can be overcome (Wen et al., 2015). Developments since 2011 include independent power sources (such as solar-powered batteries) for the camera and for sending images via wireless channels plus, of course, more powerful data analysis techniques, such as artificial neural networks, that can be trained to identify patterns in images. The newest techniques allow dozens of species from different insect orders to be distinguished from each other (Cardim Ferreira Lima et al., 2020). For a recent review detailing the strengths and limitations of camera-based traps for pest insect detection, consult Preti et al., 2020.

Automated identification is unnecessary if insects can be trapped and their images sent to computer screens for identification by expert entomologists. High-quality images are required but that is not a problem nowadays, and for human eyes, the poor orientation of targets is not necessarily an obstacle for correct identification (unless very specific miniscule features must be seen to distinguish co-occurring species from each other). Automated traps equipped with specific or generic semiochemicals and cameras have been developed and applied successfully for distinguishing different fruit fly species in images sent to human experts (Shaked et al., 2018). Shaked et al. (2018) also made attempts to automate identification of individual fruit fly species to distinguish them from other species of fruit fly and from other insects, but that has turned out to be difficult so far. Traps with fixed cameras are, of course, expensive, but owing to the miniaturization of optics and electronics, material costs are becoming lower in addition to savings in travel and time of checking the traps.

2.1.2 Mobile camera-based systems

Cheap traps photographed with mobile cameras present another option to acquire pest images automatically. Roosjen et al. (2020) used cameras fixed to traps and also cameras attached to custom-made drones (unmanned aerial vehicles – UAV) to take images of *D. suzukii* flies on red sticky trap surfaces, under various illumination conditions in the field. Deep learning methodology was applied for feature detection. The results for images taken with static viewpoint cameras were satisfactory, but the positioning of cameras on the UAV produced lower-quality images and resulted in limited success in terms of automated identification. In the field, UAVs should be operating autonomously for them to be feasible as mobile 'photographers' of traps. It would not really make sense for a person to walk in an orchard manoeuvring UAVs within their sight, as the whole idea of automated trapping is to reduce human labour, making their presence unnecessary. In a presentation on the project (https://www.abim.ch/fileadmin/abim/documents/presentations2019/ABIM_2019_7_03_Johannes_Fahrentrapp.pdf), the authors concluded that trapping efficiency must be improved and that a landing platform for the UAV must be placed in front of the trap to take better images. Even so, they concluded that deep learning, in combination with high resolution, has good potential for the detection of small insects; it is the practical technical aspects of capturing insects and acquiring high-quality images that still need to be worked upon.

A commercial example of traps equipped with pheromones or other semiochemicals and fixed-position cameras are iScout-traps. Different types of iScout-traps are available for several insect species, for example, *D. suzukii*, *C. pomonella* and *P. xylostella*, and they include a vertically placed, coloured sticky trap with a camera in front of it (https://metos.at/iscout.com). Images are sent to a web portal for analysis.

2.1.3 Tools for identifying pests with challenging taxonomic features such as flies

It seems difficult to achieve automated identification of, for example, fly species that closely resemble each other, occur together in the field, and are attracted to the same traps and whose taxonomy involves observing, for example, minute details of genitalia and hairs on the legs and body. There are as yet no reports for automated identification attempts of *Delia* spp. or *Psila rosae*. Information on probabilities of host associations may help in the identification process (Savage et al., 2016), but even so, there is room for uncertainty. The visual traps used to detect the presence and relative abundance of *D. radicum* tend to capture a lot of non-target species that also include other *Delia* species not considered as pests. By combining visual stimuli with a feeding attractant and a new trap design, KLP+ traps by CSalomon have improved the selectivity of trapping *D. radicum*. The flies are retained by glue on the surface of a transparent plastic sheet surrounding the inside of a plastic cup (http://www.csalomontraps.com/4listbylatinname/pdffajonkentik/deliaradicum.pdf). Even so, the trap manufacturer lists a couple of other Delia species, flea beetles and Ceutorhynchus weevils that are attracted to the lure, too. Thus, whenever different *Delia* species occur together in a trap, identification is complicated and requires expert skills. The same problem of non-selective traps also concerns *P. rosae*, although the orange traps (e.g. https://www.andermattbiocontrol.com/sites/products/monitoring-systems/rebell-orange.html) are the most attractive for this species and the habitus of the carrot fly is more easily recognizable than that of different *Delia* species. Among carrot pests, the identity of psyllids in traps is also difficult to verify, as species living in wild relatives of carrot can end up in the traps, too, and can only be distinguished from the carrot psyllid based on differences in male genitalia (Nissinen, 2008). The costs of developing specific identification methods for regional pests make an obstacle for R&D.

Molecular methods have been suggested as a replacement for visual identification of *Delia* sp. from traps (Thöming et al., 2017). In some cases, however, the glue in sticky traps can compromise the possibilities of molecular identification, as shown for sandflies vectoring a human disease (Halada et al., 2018), whereas for some other species, the glue of sticky traps has been considered as an excellent preservative, and did not hinder the use of molecular markers for insect identification (Chen et al., 2014; Frey and Frey, 1995). The bottlenecks lie in getting sufficient amounts of DNA easily in field conditions and having to send the DNA samples to a laboratory for processing. Rapid identification tools based on extremely small amounts of DNA are available for laboratory use, as for example, for eggs, immatures and adults of a psyllid pest of potato (Sumner-Kalkun et al., 2020). DNA can be extracted from trapped individuals with Flinders Technology Associates FTA®cards, that is, chemically treated filter papers designed for the collection, preservation and shipment of biological samples for subsequent DNA and RNA analysis. Lemmetty and Vänninen (2014) used them successfully for extracting DNA from *Bemisia* adults on sticky traps. Up to now, FTA cards for DNA extraction have been shown to work also for 11 other genera of insects including beetles, leafhoppers, flies, psyllids and aphids that were either frozen or glued on sticky traps (Pusz-Bochenska et al., 2020). The method can be used also by growers and advisors in the field, but the cards must be sent to a laboratory for analysis. DNA barcodes can be used for identification, but this presupposes that there has been adequate *a priori* identification of barcoded specimens. The study by Savage et al. (2016) on taxonomy and ecology of *Delia* spp. shows how important the understanding of biological and ecological differences in respect to herbivore–host plant associations is in order to develop the accuracy of barcoding. Differences in the ecology of different populations can be reflected also in their DNA, use of host resources and pest status.

2.1.4 Automated identification based on optoacoustics

New approaches for automated identification are emerging from domains other than the visual sensory domain. By combining the acoustic sensory domain with advanced optical detection methods, new ways of identifying fly species are emerging. The wing beat frequency of fruit flies that enter tachometer traps equipped with attractants can be detected with optoelectronic devices based on LED (light-emitting diode) light probes and transformed into frequency profiles to differentiate between the species of interest expected to enter the trap (Potamitis et al., 2018, 2017, 2015). The fundamental frequencies of the wingbeats of the flies of interest must be known and used as a reference to measure if the energy of the bandwidth exceeds a threshold. If it does, it is a verified detection. Changes in wingbeat due to temperature differences can be accommodated. Species verification can be achieved either in situ or by transmitting the recordings and performing recognition on a server. The current system makes in situ decisions about the identity of flies entering a trap for only one species. But, based on the recordings that are stored inside the trap and transmitted further, the recognition scores are greatly improved and allow for better discrimination, even between fruit fly species, although at the cost of increased power consumption and decreased algorithmic complexity at the trap level. According to Rigakis et al. (2019), the wingbeat frequencies of *D. suzukii* are included in the research group’s agenda for automated detection.

The acoustic domain is used also for differentiating whitefly species (Kanmiya, 2006, 1996; Kanmiya and Sonobe, 2002) and even sibling species of *Bemisia tabaci* from each other (Nakabayashi et al., 2017). Males of *Trialeurodes vaporariorum* and *B. tabaci* drum the leaf surface with their abdomen as mating behaviour in a species-specific manner (Kanmiya, 2006, 1996). These ‘acoustic signatures’ can be recorded with a sensitive microphone and compared with reference frequency profiles. Male acoustic signatures are likely to be used for species recognition during courtship behaviour. In the citrus whitefly, it is the females that drum the leaf surface and males orientate towards the females using vibrations as cues (Liao and Yang, 2015). Monitoring for the presence of cryptic species of *Bemisia* (that are indistinguishable on the basis of morphology), or finding mixed infestations of the greenhouse whitefly and *Bemisia*, would be possible with acoustic signatures. Of course, such a tool should be developed so that it does not require complex 'studios' to record the whitefly vibration sounds and so that ambient sounds do not interfere with the recording. The vibrations even provide avenues for controlling whiteflies (Yanagisawa et al., 2020)

2.2 Improved detection with more selective traps

Sex pheromones for monitoring and subsequently also for mass-trapping of Lepidopteran species have been available since the 1960s. Aggregation pheromones are currently also available for monitoring thrips (Kirkpatrick et al., 2017) and strawberry weevils (Cross et al., 2006b). Recently, compounds that are most likely to function as potent oviposition stimulants to female *D. suzukii* were found (Tait et al., 2020) and developed into what can be called an egg-sink that attracts females strongly even in the close presence of attractive berries on which to lay eggs (Rossi Stacconi et al., 2020a). Other functions of the compound mixture are being investigated, as the ingredients attract male flies, too. Depending on the attractive distance of the mixture to *D. suzukii*, and its selectivity, this finding can mean a breakthrough not only in monitoring the flies but also for their control through behavioural disruption.

To attract females selectively to traps, plant-derived kairomones, as attractants, have been studied intensively during the last 20 years. Such efforts have resulted in substantial advances in monitoring techniques for several horticultural pest insects (Table 4), but there is still work to do. The chemical ecology of *Delia radicum*, *D. antiqua* and *P. rosae* received a bout of research interest in the 1980s–1990s, but then there was a halt. Interestingly, since 2010, a French research group took the initiative to focus again on the chemical ecology of *D. radicum* (Kergunteuil et al., 2015, 2012; Lamy et al., 2018, 2017). They have produced new results on both attractive and repellent compounds for this species for the purpose of developing a push–pull strategy for managing the cabbage root flies. A similar bout of new research for better monitoring techniques is emerging for *D. antiqua* in Japan, Norway and the United States of America (Hoshizaki et al., 2020; Thöming et al., 2017; Willett et al., 2020).

Improving the selectivity of traps would have positive consequences for automated identification of pest species and for more efficient coverage of the sampling universe, resulting in more accurate decision-making. The following criteria for a good trap can be used to guide research on trap selectivity. Traps should: (a) specifically attract only the target pest insect, (b) be effective at capturing and retaining the majority of pest insects that come in contact with

Table 4 An overview of research and status of commercialization of semiochemicals for species included as case studies in this chapter

Species: Sex pheromone, other pheromones	Plant-derived semiochemicals (kairomones)
Cydia pomonella: Codlemone (main component (E,E)-8,10-dode-cadien-1-ol).	• Pear ester (ethyl (2E, 4Z)-2,4-decadienoate) (Light et al., 2001) used in combo traps with codlemone (Knight, 2010; Knight et al., 2019, 2014, 2005; Knight and Light, 2005a; Schmera and Guerin, 2012; Williams, 2016). Commercialized.
Argyresthia conjugella: Z-11-hexadecenyl acetate (Jaastad et al., 2002).	• Seven component kairomone mimic of rowan tree (Bengtsson et al., 2006; Knudsen and Tasin, 2015). Commercialized by Bio Innovate, SE.
Anthonomus rubi: Male-produced aggregation pheromone (grandlure I+ grandlure II + lavandulol in a 1:4:1 ratio); the mix is attractive to both sexes (Cross et al., 2006a; Innocenzi et al., 2001).	• A volatile from strawberry flowers, 1,4 dimethoxy-benzene (DMB), increases the attractiveness of the aggregation pheromone to both sexes of *A. rubi* (Baroffio et al., 2018; Mozūraitis et al., 2020). Commercialized.
Drosophila suzukii: A synthetic volatile blend based on six compounds found in the skin of egg-infested berries is attractive to both sexes. Commercialization in progress. (Kaiser et al., 2021; Rossi Stacconi et al., 2020a,b; Tait et al., 2020).	• Several types of odours of fermentation, microbial, fruit, and leaf origin attract the flies (Cloonan et al., 2018) and have been developed into commercial products (Cha et al., 2018; Frewin et al., 2017; Harmon et al., 2019; Kirkpatrick et al., 2017; Tonina et al., 2018; Zerulla et al., 2016).
Delia radicum: None known so far.	• Allyl-isothiocyanate, a feeding attractant (Finch and Skinner, 1982; Nottingham, 1988; Nottingham and Coaker, 1987, 1985) in a Coaster Lure Packet is used in a new trap design by CSolomon, resulting in increased selectivity of the trap for the flies http://www.csalomontraps.com/4listbylatinname/pdffajonken-tik/deliaradicum.pdf. • Oviposition stimulants have been found (Gouinguené et al., 2006; Kergunteuil et al., 2012). • Plants attractive to flies are characterized by high release rates of distinct terpenes (Kergunteuil et al., 2015).

Plutella xylostella: (Z)-11-hexadecenal (Z 11-16:Ald), (Z)-11-hexa-decenyl acetate (Z11-16:Ac), (Z)-11-hexadecenol (Z11-16:OH) (Chow et al., 1977; Koshihara et al., 1978).	• Allyl isothiocyanate is a feeding attractant (Gupta and Thorsteinson, 1960) and an oviposition stimulant. • Isothiocyanate iberin and sulforaphane are potent oviposition stimulators (Renwick et al., 2006). • Plant-derived kairomones have been tested in combination with the sex pheromone (Dai et al., 2008; Li et al., 2012; Miluch et al., 2014; Reddy and Guerrero, 2000).
Delia antiqua: None known so far.	• n-propyl disulfide, n-propyl mercaptan are oviposition stimulants at short range (Ishikawa et al., 1978). • Methyl propyl and dipropyl trisulfides have attractant-oviposition stimulating activity (Matsumoto and Thorsteinson, 1968). • Decomposing onion bulbs are a potent attractant for adult flies, but a 2-phenylethanol + n-vakeric acid mixture captures flies 1.8–5.0 times more effectively (Ishikawa et al., 1984).
Psila rosae: None known so far.	• Both sexes respond to a number of volatile plant constituents from Apiaceae (Guerin and Visser, 1980). • Propeny-benzenes oftans-asarone and hexanal treated sticky traps increase fly catches synergistically (Guerin et al., 1983). • Oviposition stimulants have been found (Degen et al., 1999). • 2-phenylethanol and n-valeric acid embedded in silicon rubber bulbs worked as attractant in field tests (Ishikawa et al., 1987).
Whiteflies: A female sex pheromone identified by Yin and Maschwitz (1983) was developed into a (proto-type?) lure attached to yellow sticky trap by Chinese researchers (Wang et al., 2011)	• High nitrogen changes the profile of tomato volatile organic compounds (VOC) and attract *B. tabaci* (Islam et al., 2017). • Repellent terpenoid compounds have been identified (Bleeker et al., 2012, 2011). • Volatile Organic Compounds (VOCs) attractive to *T. vaporariorum* were identified from tomato and eggplant cultivars (Darshanee et al., 2017).

the trap, (c) provide early detection of the pest insect and (d) allow correlation of trap catch with subsequent crop infestation (Cloonan et al., 2018). When many attractive substances are available, as is the case for *D. suzukii*, odour cues from different sources may interfere with each other and reduce the pest's attraction to otherwise attractive odour combinations – a risk to be taken into account (Cloonan et al., 2019). On the other hand, the case with *Anthonomus rubi* shows that multi-pest traps are possible when the attractive compounds are specific enough for the different target pests, in which case they do not interfere with each other (Baroffio et al., 2018; Fountain et al., 2017).

Inspired by inconsistencies and high variability in trapping *C. pomonella* with sparsely placed sex pheromone traps, a new concept of understanding the interaction principles between traps and pest insects was developed recently (Adams, 2017; Miller et al., 2015). The new concept aims at being able to estimate absolute – instead of only relative – population densities in the landscape. This is done by specifying the attractive plume radius of the attractants and the proportion of target insects caught by the trap per areal unit. One outcome from the new concept is a recommendation for placing sex pheromone traps in line close to each other to reduce the variability of catches that are a problem when single traps placed far apart are used for trapping *C. pomonella*. Line trapping offers savings in time and cost when servicing aggregated versus distributed traps (Adams, 2017). Specific action thresholds were developed for the pear ester trap and compared with those of sex pheromone traps. Traps equipped with the kairomone pear ester improved female catches and predicted the egg hatching time of *C. pomonella* better than codlemone traps. The prediction improvement was based on cumulative degree-day totals required from Biofix until egg hatch: the degree-day totals had the lowest variability when the Biofix was based on the sustained catch of female moths in a pear ester-baited trap (Knight and Light, 2005b).

Trapping studies with *D. suzukii* show that lure attractiveness and selectivity can change during the season in relation to environmental temperatures and phenological, developmental and physiological stages of both the pest and its host plants. Different lures must be implemented in different periods and for different purposes, that is, for monitoring or mass trapping (Rodriguez-Saona et al., 2020; Tonina et al., 2018; Wong et al., 2018). The plant background can significantly influence trap catches, as shown for *D. suzukii* (Cha et al., 2018) and *A. conjugella* (Cha et al., 2018; Knudsen et al., 2017; Knudsen and Tasin, 2015). Thus, the same lure is not always appropriate in all contexts. The potential for trap catches to predict the density of larval populations depends on the crop species, pest generation, and density and geographical region, with variations due to climate and natural enemy complexes. Unique pheromone-based predictive models may be needed in different growing regions where the climate and the responses of the moths to pheromones vary. Furthermore, the presence and composition of natural enemies influence the relationship between trap catches of moths and the density of moth immature stages; therefore, a weighing factor is needed in the predictive model to take the effect of natural enemies into account (Miluch et al., 2013).

Depending on the target species, traps integrating both visual and olfactory cues can be superior tools for monitoring (Kirkpatrick et al., 2017). Trap design can have a crucial effect on trap catches as shown for *D. suzukii* (Kirkpatrick et al., 2017) and the multispecies trap for *A. rubi*, *Lygus* sp. (Fountain et al., 2017) and *D. radicum* (http://www.csalomontraps.com/4listbylatinname/pdffajonkentik/deliaradicum.pdf).

2.3 Remote sensing for reducing sampling time and overcoming sampling problems caused by patchy pest distribution

Most horticultural pest insects and mites are aggregated spatially. This is a nuisance when developing sampling plans: patchy distributions make accurate estimates of populations difficult, resulting in the implementation of the wrong management strategy. The seemingly more economical approach of taking fewer than the recommended number of samples has little value, because the representativeness of sampling suffers (see Table 2) and information is lost through apparent savings in human labour and time investments. A good example is *P. xylostella* in vegetables in Australia: stakeholders tend to favour fixed sample sizes, but even so, they take too few samples. This preferred sampling plan was shown to erode the criteria for reliable decision-making (Hamilton et al., 2006), although simpler and more time-saving sampling protocols are available (Hamilton et al., 2004) but seemingly do not match the criteria of stakeholders.

The effect of a patchy distribution also concerns phytophagous mites (Zahner and Baumgaertner, 1984), adult and immature whiteflies in, for example, tomato (Kim et al., 2001; Park et al., 2011b), eggs and consequently root-inhabiting maggots and pupae of cabbage root flies in cabbage fields (Bligaard, 1999; Finch et al., 1978, 1975), the carrot fly (Jens, 1983), eggs and onion maggots infesting the roots of seedlings and later the swollen plant part sitting on the soil (Whitfield et al., 1985) and larvae of *P. xylostella* that consume different types of *Brassica* vegetables (Chua and Lim, 1979). Automating the sampling or detection of patchily distributed pests or plants infested by them would be a desirable option to obtain sufficient numbers of observations with less time and labour. Such automation could concern either in situ counts of the pests themselves or measuring plant responses to the presence of the pests, that is, biotic stress.

Instead of farmers walking their crops, drones could do the sampling when this requires in situ counts or observations, particularly in very large cultivations.

Up until now, most research on the use of drones for crop protection purposes has focused on disease detection through plant phenotyping using multispectral, hyperspectral, RGB (red, green, blue), fluorescence and thermal images of canopies as well as landscape and habitat features (Gogoi et al., 2018; Zhang et al., 2019). In situ counts of insects from plants using cameras attached to drones are much more difficult. Illumination, angle of capture and shadows can significantly interfere with pest or symptom detection in images taken with drones. Furthermore, the visual and spectral cues used to detect pests may be the result of several different factors, including other insect species than the target ones that may be present in the crop. Therefore, verification by other methods of species detection is often necessary (Barbedo, 2019).

There have been, however, some proof-of-concept type experiments which suggest that drones could have a bigger role in sampling or monitoring horticultural pest insects, either for research purposes or for purposes of actual crop protection. Aerial thrips have been sampled with the help of sticky, customized Petri plates attached to a drone, to study trivial and long-distance dispersal of thrips above onion fields (Smith et al., 2015) and to monitor several insect species from the air above rice fields (Kim et al., 2018). Drones can also carry a sweep net and sample insects from vegetation in otherwise inaccessible places (Löcken et al., 2020) or fields that are too large to sample by walking (Kovanci et al., 2005). The same approach could be used to sample adult *P. xylostella* in *Brassica* vegetables, and even insect larvae can be sampled as shown by Löcken et al. (2020). Adult carrot flies and cabbage root flies move between crop fields and their surrounding habitats daily. Drone sampling may help to detect details of these flies' dispersal and local migration behaviour, for which studies on sampling aerial thrips with the help of drones pave the way for (Smith et al., 2015). In vineyards, drones are being developed for monitoring *Phylloxera* by taking hyperspectral, multispectral or RGB images of the foliage and correlating reflectance spectra with pest densities (Vanegas et al., 2018). Mini drones have even been developed as artificial predators for monitoring and killing moths in greenhouses (https://pats-drones.com/). For research purposes, drones equipped with UVA sensors could be used for detecting insects treated with fluorescent substances in ecological studies, for example, for finding out how insects move in their habitats or between habitats (Teickner et al., 2019). Fixed traps equipped with sensors measuring abiotic conditions in the monitoring area contribute to data collection on factors influencing pest occurrence and reproduction and may eventually be integrated with forecasting models for pest occurrence and population dynamics.

Infestation by phytophagous mites, aphids and whiteflies causes changes in the spectral reflectance of leaves and canopies. Detection of such changes has already been shown to be possible in soybeans infested by aphids (Marston et al., 2020) and whiteflies (Barros et al., 2021). The same methods are applied in greenhouses for pest detection through stress symptoms in plants, with the help of drones (https://www.greenhousemag.com/article/the-drones-are-close/). Pats drones have developed a phone-based app that uses GPS and mapping software to autonomously fly a drone to points in a field selected by the farmer. The images taken by the drone are interpreted by the app to provide an accurate green area index (GAI) and to count emerging plants. The quality of the image collected also is good enough to identify weeds and is claimed to be sufficiently accurate to capture insect damage on a single leaf (https://pats-drones.com/). In horticulture, low-growing crops such as cabbage, strawberry, onion and lettuce are the easiest candidates for monitoring using drone-based cameras to detect pests or their symptoms. Tall crops such as fruit trees, tomato and cucumber or berry bushes can be more challenging, due to their more complex vertical structure.

With remote sensing and AI, it has become possible to use plant, field and regional scale phenotypic information and integrate it into predictive and prescriptive management tools for monitoring, mapping and predicting outbreaks (Jung et al., 2021). When the whole field can be covered with remote sensing, implementing sampling plans that take the pest spatial distribution into account will decrease in importance. The remote sensing techniques include ground-based spectroradiometers, aerial photographic cameras, airborne digital multispectral and hyperspectral imaging systems, and moderate and high-resolution satellite imaging systems (Abd El-Ghany et al., 2020; Prabhakar and Thirupathi, 2018; Yang and Everitt, 2011). Radar-based technologies make a group of their own that is ground based but focuses on detecting insects in the air even in the night time so that it is possible to detect insect migrations in the dark (Abd El-Ghany et al., 2020; Prabhakar and Thirupathi, 2018).

The reviews by Abd El-Ghany et al. (2020) and Prabhakar and Thirupathi (2018) list the different vegetation indexes that are used to measure the stress level of plant canopies and what kind of stress types the indices can reveal. Glenn and Tabb (2019) compared different methods of determining the NDVI (normalized difference vegetation index) for apple trees. They concluded that NDVI is a useful tool when evaluating long-term crop changes such as pest damage, chronic water shortage and nutrient deficiencies that affect chlorophyll, whereas NDVI is not useful for acute stresses such as an irrigation pump failure or plugged irrigation lines that have an effect within days. Overall, remote sensing techniques for detecting pests or pest-caused changes in apple trees are not very advanced yet (Park et al., 2021), although the use of reflectance indices in leaves infested by different densities of mite pests was studied already in the 1990s (Penuelas et al., 1995), and a review of remote sensing and geospatial techniques for fruit tree management was published in 2010 (Panda et al., 2010).

Pests, diseases and their impacts on plants can also be detected based on the chemicals the infested plants emit into the air. E-noses are suitable for monitoring when they provide information on pest presence at a time when it is still possible to initiate, continue or intensify control actions. The use of e-noses is greatly enhanced by AI-based pattern recognition algorithms. There are, however, still challenges to overcome regarding sensor performance, sampling and detection in open areas, and scaling up measurements, as reviewed by Cui et al. (2018) from the point of view of IPM in vegetables and fruit trees.

An important advantage of visual and thermal remote sensing techniques, particularly those based on aircraft and satellites, is the improvement of spatial and temporal resolution compared with traditional methods for pest monitoring such as traps of different kinds or in situ counts. A disadvantage is that the remote-sensing tools tend to be expensive to use in small areas, particularly when time-series are the goal. Aerial images particularly are costly if repetitive imaging is required to study canopy status. Technical issues include distortions in images due to the relative motion of sensors and source. The glasshouse environment can be challenging for day-time spectral remote sensing because of inconsistent lighting, spectral scattering and shadows caused by glasshouse structures. Such problems were overcome when the images were taken after sunset with an active light source (Nguyen and Nansen, 2020). With this innovation, leafminers in the leaves of bok choy and spinach could be detected with >99% accuracy. Lastly, data processing requires specialized training for analysis of images (Prabhakar and Thirupathi, 2018).

Crop pests and diseases commonly occurring in continuous cropping pattern zones are best amenable to remote sensing, whereas crop pests/diseases that occur sporadically in time and space are less amenable to be monitored by remote sensing (Rao and Lakshmikantha, 2020). Because remote sensing of pests cannot be cost-effectively or technically applied to all pest species, the approach taken to evaluate its possibilities in detecting and forecasting pest insects in China is worth bringing up. Cock et al. (2016) compiled tables on symptoms, thresholds for action and options for pest management responses of main agricultural insect pests in important crops. Chinese cabbage represented horticultural crops in the study. The authors used the tables, among other things, to evaluate the scope for remote sensing of the pests in China and how the information generated or forecast would be used to improve pest management by existing agricultural extension services. Among the insect pests and diseases important in Chinese cabbage, three were concluded to benefit from the use of remote sensing: one viral and one fungal disease and the diamondback moth *P. xylostella*. The authors also list the currently existing ETs and intervention options for the pests of biggest importance and in so doing integrate with each other the need to adapt such thresholds with the new technology. For example, correlations must be produced for results of remote sensing based on vegetation indexes or hyperspectral profiles and associated pest densities to enable decision-making concerning intervention needs.

Results of remote sensing can be integrated into robotic platforms such as autonomously moving trolley-mounted robots or robotic platforms in greenhouses. The Ecoation robotic platform includes, among other things, an optochemical method for detecting the presence of whiteflies in tomato (https://www.ecoation.com/) based on changes in plant chemistry. Another example of the use of robots for the same purpose is the Greenpatrol-robot under development in Spain for use in tomato and cucumber crops in greenhouses (http://www.greenpatrol-robot.eu/Greenpatrol-robot). A user interface can be accessed by farmers to determine the robot's status and see a map of healthy and infected zones together with recommended actions. The robot is capable of identifying where pests are located and of returning to treat them. Under the farmer's instruction, the robot has the ability to spray the plant with pesticide. Scanning of the greenhouse by the robot is based on IPM strategy algorithms. There is no information, as yet, whether the system will at some point also include natural enemies as recommended actions.

2.4 Nano-inspired biosensors for plants

Various nano-inspired biosensors have been reported that range from detection of plant infections (fungal, viral and bacterial), abiotic stress, metabolic content, phytohormones, miRNAs, genetically modified (GM) plants to transcriptional and genetically encoded biosensors in a very short time span (Giraldo et al., 2019; Kumar and Arora, 2020). Combined with abiotic data at a microenvironmental level, the nanosensors would make a good reporting tool about the status of the crop in terms of plant health, as so called 'plant wearables'. A plant wearable can consist of an ultrathin and ultra-lightweight nanosensor, the aim being to attach flexible sensor devices directly on plant tissues such as leaves for continuous monitoring (Li et al., 2020). It is too early to tell whether they can be used for detecting horticultural pest insects and mites. They would probably complement, or replace, spectral imaging tools as biomarkers for detecting symptoms caused by various stressors, but it is not clear how closely they can fingerprint to give the stressors' identity. Sampling plans must be developed with a good understanding of the spatial distribution of the pest species and the criteria that must be fulfilled to achieve reliable information about pest occurrence in the field or greenhouse.

Owing to their small size, nanosensors could in principle be 'sown' on the crop in large numbers, or they could be taken to the crop and attached there according to a sampling plan that has a clear goal. If biotic stressors are detected only on a presence–absence basis in a few locations, there is a danger of the concept of the EIL and ET becoming obsolete. That threat notwithstanding, nanostructure-supported non-invasive detection tools combined with smartphones pave the way for fast and on-site diagnosis of plant diseases and long-term monitoring of plant health conditions. Such solutions are desirable particularly in resource-poor settings (Li et al., 2020). A potential application could be nanosensors attached to plants for detection of whitefly-induced biochemical changes in plants. The changes are systemic, and detection could be improved by placing the sensors in the top and middle layer of vertical plants to target leaves with L3 and L4 immatures and adults that induce the strongest local and systemic biochemical changes in the plant (Estrada-Hernández et al., 2009).

2.5 Natural enemy adjusted thresholds (NEETs)

Decision-making solutions (sampling plans and EILs and ETs) developed in the 1990s for managing phytophagous mites in apple have paved the way for new research that aims to include natural enemies in sampling plans and EILs (Nyrop, 1988; Park et al., 2000; Van Der Werf et al., 1994). Van Der Werf et al. (1994) developed a sequential sampling program for phytoseiid predators of mites in apple and continued the program development by modelling predator:prey ratios for phytoseiids and phytophagous mites in the same crop (Van Der Werf et al., 1994). Action thresholds for tetranychid mites in some ornamental plants were developed by incorporating phytoseiid mites as their control agents (Alatawi et al., 2005; Opit et al., 2003). Later on, Zhang and Swinton (2012, 2009) undertook pioneering work by developing natural enemy adjusted thresholds (NEETs) for soybean aphids in the United States of America. They introduced a new decision rule for judicious insecticide decisions using NEETs. The new threshold represents the pest population density at which insecticide control becomes optimal in spite of the opportunity cost of injury to natural enemies of the target pest. Bannerman et al. (2015), also working on soybean, in Michigan, compared the relative bias, precision and efficiency of sampling methods for natural enemies of the soybean aphid. Such studies are still rare though, and an additional challenge is that NEETs require modelling and computer skills. Tran and Koch (2017) determined the spatial patterns of predators of a pest aphid. Decision support systems are considered to be necessary for implementation of NEETs, as otherwise turning sampling results into decisions is too complicated. Automated sampling and identification is unlikely to become possible for all species of pest and their natural enemies; despite this, sampling plans should be as practical as possible in terms of the time and labour resources required.

It is the farmer who takes the risk of adjusting her plant protection strategy that may or may not involve natural enemies, and her decision concerning investment in biological control has repercussions concerning pesticide residues in food and the environment as well as the economics of the farm. Traditional cost–benefit analysis may not be good enough to estimate the socioeconomic costs and benefits of such investments comprehensively. How does the farmer, then, know whether it would be good for her or not to invest in using biological control? This question was recently addressed by Benjamin and Wesseler (2016), who used the maximum incremental social tolerable irreversible costs (MISTICs) as a tool for such evaluation. The output of the MISTIC modelling tool is an estimation of when the incremental reversible benefits of the IPM strategy that includes biocontrol outweigh possible irreversible costs of such a strategy by a minimum threshold. Only when the minimum threshold is exceeded should introduction of biocontrol as part of farm-level IPM be considered. At the same time, the output informs us how the individual farmer's decision influences society. The results obtained by Benjamin and Wesseler indicate that including biocontrol in potato, but not in maize, IPM is feasible. According to the authors, the reasons behind biocontrol being more feasible in potato could be lack of adequate pesticide control of diverse pests in potato, the sensitivity to residue-free products by society and the regulated use of IPM by authorities. Although theoretical, the modelling study by Benjamin and Wesseler highlights how the changed context that is likely to involve reduced efficacy and availability of pesticides changes the premises of making decisions concerning the adoption of alternative pest management strategies. Predicting the costs and benefits of biocontrol at the farm and societal level gives impetus to develop and target the development of NEETs at the crop level.

2.6 The value of information, sampling plans and economic/action thresholds: the cases of **P. xylostella** *and* **T. absoluta**

Three papers from three different decades together highlight important issues that were brought up in the overview of bottlenecks and the challenges of monitoring and forecasting. The first is that when sampling for decision-making, there is a lower limit for the number of samples that must be taken to obtain reliable information for decision-making, whereas the maximum number of samples can be adjusted and resources thus saved. The second issue is that stakeholders tend to prefer fixed-size sampling with so low sample sizes that such sufficient information is not obtained. The third issue is farmers' risk aversion that tends to result in ignoring sampling results that recommend no action.

The issues culminate in the following questions: (1) which types of sampling plan give precise enough results for decision-making in practice and optimize the net value of sample information but would still be acceptable to users in terms of practicality; (2) how should ETs actually be implemented – as top-down recommendations that must be strictly followed or as learning tools that are developed together with the stakeholders through a bottom–up principle and that give room for the peculiarities of human risk aversion and associated decision-making style; and 3) how to support farmers in the implementation of sampling plans that may first seem complicated, but which in effect are quite practical and information laden at the same time? These questions concern sampling that requires in situ counts of pests in the crop, as they are considered more time consuming and laborious compared to using traps that concentrate pests in one or more locations.

'Sequential classification sampling plans' were strongly recommended by Binns et al. (2000). Sequential means that the sample size is not predetermined. Instead, the decision of whether to make a decision (intervene or not) is made during the sampling process, based on the cumulative counts of pests in samples collected so far. There must be some criterion with which to compare the cumulative count, of course, to be able to know if more samples must be taken or if sampling can be stopped and a decision taken. The person assessing the crop takes samples and checks whether the cumulative count of insects is below or above the stop boundary after every sample.

There can also be two stop boundaries, in fact; in this case, the sampling is called 'tripartite classification sampling'. With 'sequential tripartite classification sampling', the farmers get more information: depending on where they end up with the cumulative sample size, they must either intervene now or not intervene, they also receive a recommendation for when they should sample again on a later date (e.g. after 7 days). Because the sampling result now informs the farmers about future actions, so that the sampling plans are 'chained' in time, a tripartite sampling plan is also called a 'cascaded tripartite classification sampling plan'. If the sampling plan can advise the farmers reliably about when in the near future the next sampling bout should be undertaken, and the interval (e.g. being 7, 14 or 21 days) between current and future sampling plan depends on the current sampling result, the sampling plan is called 'adaptive frequency classification sampling' Nyrop et al. (1994). Cornell University produces tripartite classification sampling plans for apple growers for decision-making concerning the management of the European red spider mite (Anonymous, 2020). The plans are presented as charts and with instructions on how to undertake the sampling and how to compare the sampling results with the chart for decision-making.

Precision of a sampling plan refers to SEM/m, the ratio of the standard error to the sample mean (Green, 1970). A fixed, or predetermined, precision level of 0.25–0.30 is often considered sufficient for decision-making purposes in IPM. The total number of samples needed to be taken depends, then, on the degree of precision required. In sequential sampling, sample size is greatest when the population is estimated to be within a critical range of densities at which treatment may be necessary – it is not desirable to make a wrong decision.

Sample size is less when the population estimates are well above or below that range. The goal is to achieve acceptable sampling precision with minimal effort. In this way, situations of taking unnecessary samples can be avoided in contrast to fixed-size sampling plans, where the same number of samples is always taken (Binns et al., 2000; Pedigo and Buntin, 1993).

Because sequential tripartite classification or adaptive frequency classification sampling protocols give much more information to the grower than simpler sampling plans, in addition to that they save sampling resources, they were considered by their creators (Binns et al., 1996; Binns and Nyrop, 1992; Nyrop et al., 1994, 1989, p. 1989; van der Werf et al., 1997) to be much more valuable than traditional fixed-size sampling plans. But their reception among farmers has not been particularly encouraging as they can be considered too complicated by the practitioners. The same concerns variable intensity sampling plans, where sampling intensity (how many sampling units are taken) is reconsidered after every sampled segment of the sampling transect and which also fulfils the criterion of representatively sampling throughout the field (Pedigo and Buntin, 1993) (see also Fig. 3).

Monitoring the diamondback moth in broccoli fields in Australia at the beginning of the 2000s brought up the issue of sequential sampling again. Hamilton et al. (2004) developed a sequential sampling plan for the moth larvae. The plan used a dynamic action threshold that accounted for factors such as the prevalence of parasitism, crop growth stage and intended market destination. It was presented as a computer program. After a couple of years, it turned out that the sequential sampling plan was not used: it was considered too complex, and stakeholders preferred fixed-size sampling plans, but took usually only 10–20 samples per field, which according to Hamilton was clearly too few to produce reliable results. Furthermore, only a small part of broccoli fields was covered by such low sample sizes, thus sampling violated the criterion of representativeness. Sequential sampling plans demand that at least a minimum sample size always be taken from a field to satisfy the criterion of representativeness. To achieve even better representativeness, a variable sampling plan (see Fig. 2) can be applied.

In Hamilton's case of sampling for *P. xylostella*, he showed that to achieve a good enough level of precision using a fixed sampling size, at least 45 samples should be taken per field. This was in contrast to the industry standard of fixed sample size of 10–20 samples per field, too few to result in reliable decision-making. Hamilton et al. (2006) also showed that depending on the lower or higher action threshold (larvae per plant) used for decision-making, the probability of making type II error (not treating when there would be a need to treat) was higher for the lower AT, particularly if the sample size was too small (Hamilton et al., 2006). This meant that when taking only a few samples, risk aversive growers (who wanted to intervene at lower pest densities) were actually making the type II error more often than growers who accepted higher pest densities before intervening. Thus, the appropriate sample size is dependent upon both the AT and the level of type II error that one is prepared to accept. The question then becomes: what should be done to encourage the implementation of reliable and at the same time less resources-demanding sampling plans by the stakeholders to really help their decision-making?

Giles et al. (2017) offered an answer to the above question: 'These thresholds are more likely to be utilized by stakeholders when integrated into dynamic web-based IPM decision support systems that summarize pest management data [and push site-specific biological control management recommendations to decision-makers].' A very interesting approach to answer the same question was offered recently by Rincon et al., (2020), who also ended up recommending IT-based support systems – albeit in a less complicated form than that of Giles et al., to encourage farmers to take up more reliable sampling plans. However, their approach went deeper into the socioeconomic issues that may hinder implementation of sampling plans. They began with the issues concerning uncertainty and the value of information, and the time constraints of farmers and their risk aversion, but addressed also the issue of fixed ETs which in reality vary according to the variation in product price in particular.

Rincon et al. (2020) worked on a tomato greenhouse infested with *T. absoluta*, undertook intensive sampling in the crop to first determine explicitly the level of infestation, and then evaluated two sequential and two variable-intensity sampling (VIS) plans for the classification of pest density, by letting farmers do the sampling and measure the time needed for sampling. The re-sampling was undertaken both with computer simulations and by field trials. As a result they suggested a new approach to ETs: that they should be seen not as fixed recommendations but as *learning tools*. With the help of such a learning tool, the farmers can determine their own threshold, keeping in mind the reference, but at the same time adjusting their decision-making according to their experience, intuition and knowledge about market developments.

Eventually, Rincon et al. (2020) recommended variable intensity sampling, not sequential sampling. The value of the information produced by VIS was the highest, and the time needed for sampling was no more than that needed for binomial presence–absence sampling. The merits of the study by Rincon et al. (2020) are in their collaborative approach to developing the sampling plan and doing an intensive sampling first and in using it as a reference for the farmers, who tested the four different sampling plans. The farmers learned about the level of uncertainty of the sampling results directly and could themselves consult their risk-averse selves with regard to decision-making. However, they were equipped with objective knowledge about the pest situation. Rincon et al. (2020) concluded that implementation of the adaptive sampling plan requires simultaneous technological developments to make real-time calculations and deliver the information in an appropriate format. They foresee apps that will do the calculations for the sampler, as they must get instruction to continue or not continue sampling 'on the go'. In such situations, documentation based on voice recognition would be of great help as it frees the grower's or advisor's hands for actual work.

It must be noted that sampling based on counts in situ turned out to be adequate for a pest like *T. absoluta*, where the larval mines in leaves are easily seen and counted. VIS sampling that is based on counting specimens may not be the best option for pests such as whiteflies that are more difficult to see. VIS can be implemented also with presence–absence sampling, in which case the difficultly of counting very small and prolific specimens is avoided. Furthermore, automated counting methods like the app that recognizes either adult or immature stages of whiteflies (Anonymous, 2021) is exactly what is needed for situations like this, and such tools, once available for use in the field, can play a decisive role in the willingness of stakeholders to adopt a sampling plan.

2.7 Forecasting

Innovations regarding mechanistic models and advances in statistical models brought about by the use of AI and associated growing importance of Big Data and data quality are some of the key developments in forecasting for IPM. These developments concern not only horticulture but primary production in general. Several authors emphasize 'seeing the wood for the trees', that is, moving from reductionist mechanistic models towards more systemic or holistic approaches to modelling as a tool of pest forecasting in IPM. Harvey (2015) calls for Big Data for conducting meta-analyses and constructing powerful models for IPM in temperate horticulture. Orlandini et al. (2017) describe the need to develop agroclimatology-based mechanistic models in terms of how models are built, parameterized, validated and implemented to produce, as outputs, pest risk maps for long-term decision-making and preparedness, and pest forecasts for day-to-day decision-making. Tonnang et al. (2017), Baker et al. (2018) and Orlandini et al. (2017) all emphasize the creation of a modelling culture that should involve model developers, service providers (e.g. for weather data) and final users.

New approaches to data analysis such as Big Data algorithms emphasize collaboration between computer scientists and biologists. The literature is replete with reviews about Big Data and its possibilities, but what is really needed for pest forecasting are more empirical cases of the use of Big Data for improving forecasting at wider temporal and spatial scales than before. This need poses new requirements for multidisciplinary collaboration and for being able to identify what types of data are relevant and valuable now, even though they may not have been so before. This requires also that the importance of data collecting must be made understood to all stakeholders. Otherwise a large part of important data could remain only anecdotal and not become used (Harvey, 2015).

Orlandini et al. (2017) call for coupling of pest models with crop models, that is, a step towards a more systemic approach, since many current pest models do not have outputs that are easy to translate into pest impacts. They foresee also an increasing quantity of pest observations and a move toward the concept of big data and associated technologies for capturing, storing, managing and analysing data. Such a move is expected to result in a changed balance between mechanistic and statistical forecast models, as depicted by (Baker et al., 2018). A thorough understanding of mechanisms behind biological and ecological processes is still needed instead of mere working with 'black boxes' associated with statistical models. Developments in both modelling approaches are foreseen to better use them together, and thus get more out of the combination of deductive and inductive modelling approaches. Mechanistic models could be used by machine learning algorithms both as transient inputs and as a validating framework. (Baker et al., 2018).

At the same time, technical developments in remote sensing are also making mechanistic models more powerful by helping to get better data for model validation. One limitation of mechanistic weather-based phenology models has namely been that data sets of in situ temperature are very specific to the locality of weather stations, that is, the data have a low spatial and temporal resolution. Satellite-based remote sensors that continuously measure land surface temperatures over vast areas can nowadays be used for creating more accurate degree-day accumulation maps for large areas. One example is given by the studies of Marques da Silva et al. (2015) on *T. absoluta* in Portugal. Remotely measured land surface temperature data was combined with the threshold temperature and thermal constants of *T. absoluta* development. The outputs were risk maps depicting the number of generations produced by the pest in different parts of the country with respect to the spatial and temporal variation of degree-days sum. The authors found that the spatial resolution of such maps was better than those produced with in situ weather stations. Such resolution improvement can make a difference in site-specific management of the pest. The authors foresaw an early warning system that could geographically locate farmers associated with similar climatological patterns and could warn them when higher risk levels are reached.

At a smaller scale, precision agriculture technologies enable predicting the zoning of pest prone areas within fields for pests that have aggregated distributions. There are methods to partition fields in management zones, but zoning for pest management purposes requires spatially explicit ecological layers that are created on the basis of a pest's within-field distributional patterns.

Such layers represent a species' ecological niche. The patterns, or zones, are generated via species distribution modelling (SDM) and high-resolution environmental data using tools such as drones and wireless sensor networks to map environmental conditions with high spatial and temporal resolutions. Méndez-Vázquez et al. (2019) delineated site-specific pest management zones in a lime orchard using SDM by first mapping pest-driving environmental features within the orchard via precision sampling tools. These measurements served as raw data for creating the spatially explicit ecological layer needed for predicting where selected pests would thrive. They worked with six virtual pest species (with known affinity to lime trees) and mapped, in a correlative manner, their known distributional ranges within the experimental orchard using a subset of real environmental predictors. Lastly, they evaluated the performance of the selected zoning models in terms of multivariate similarities between environmental preferences of pests and environmental characteristics of individual management zones. The authors concluded that the use of the ecological layer that was created for purposes of identifying pest management zones according to the environmental requirements of the pest species worked better than the classical zoning methods. The approach appears rather demanding in terms of measurements that need to be done but may be feasible to do in long-term habitats such as fruit orchards.

Tonnang et al. (2017) give an overview of advances in crop pest forecast modelling and present such approaches based on advanced mathematics, computer and physics theories. These approaches include artificial neural networks, cellular automata coupled with fuzzy logic, fractal, multi-fractal, percolation, synchronization and individual/agent-based approaches. Most of the new types of modelling tools presented by Tonnang et al. (2017) concern spatio-temporal dynamics of pest distributions and densities. For example, a cellular automata modelling was used to predict the risk of the invasion and natural spread of *T. absoluta* from Spain across Africa. The output revealed that *T. absoluta* could reach South Africa 10 years after being detected in Spain (Guimapi et al., 2016). The cellular automata model integrated NDVI, temperature, relative humidity and yield of tomato production. Artificial neural networks (ANN) are showing good promise in predicting pest dynamics more accurately. Examples include predictions for population densities of *P. xylostella* and its ichneumonid parasitoid *Diadegma semiclausum* (Tonnang et al., 2010) and forecasting paddy stem borer population occurrence (Yang et al., 2009). More recently, Yan et al. (2015) compared multiple regression (MR) and ANN for predicting monthly pest risks of *Thrips palmi* and *P. xylostella*. MR is the simplest and most widely used method for pest-risk prediction. The advantages of ANN are that the modelling can be conducted without prior knowledge: any relationship between given predictors and dependent variables can be learned by the neural networks, regardless of linearity or non-linearity. Non-normally distributed data, multicollinearity issues and data noise are also tolerable when training the network. But when using ANN, the importance of predictors to a given dependent variable cannot be explicitly identified by ANN as it performs like a black box.

Yan et al. (2015) list a number of characteristics of MR and ANN that have importance for the modelling process and output. These authors are among those that see benefits in combining the mechanistic and statistical modelling approaches. MR could be used to identify key variables that contribute to pest development, that is, MR can open up the black box that ANN cannot do and can reduce the model complexity and improve the training efficiency and/or accuracy (Yan et al., 2015). Likewise, Kumar et al. (2018) also found out that ANN produced more accurate outputs than classical regression in predicting incidence of two rice insect pest species and one natural enemy species using weather variables as inputs. ANN and fuzzy logic were used also to predict daily risk of the western flower thrips in roses grown in greenhouses using only four variables in comparison with earlier models that needed a large number of variables to produce desired output (Tay et al., 2020).

D. suzukii exemplifies several of the issues that Magarey and Isard (2017) list in their troubleshooting guide concerning mechanistic forecasting models. As *D. suzukii* is an invasive species, the biggest of problems or gaps concern details of its biology and ecology, but also a validation of models that predict the development of its life stages or fitness in the new regions of its distribution. Degree-day-based models and stage-structured models are not always validated to see how well they predict the inter-annual variation in the activity of the pest. Initial population development after invasion, survival at temperature extremes, and conditions necessary for the development of damaging populations are not known well enough to use these details as input for models. Existing models may rely on development measured in laboratory experiments (Kinjo et al., 2013; Tochen et al., 2016) instead of utilizing field detection data from traps or fruit samples. Data on winter survival and spring populations of *D. suzukii* in regions with cold winter conditions are limited (Dalton et al., 2011; Shearer et al., 2016; Stockton et al., 2018); thus, there is a need to further evaluate and predict fly activity using field-collected data on adult flies. The age structure of estimated populations suggests that trap and fruit infestation data are of limited value for validating models concerning the fly's development (Hamby et al., 2016; Tochen et al., 2016; Wiman et al., 2014). Despite these issues, *D. suzukii* activity was concluded to be predictable and environmental conditions (such as the annual number of days below 0°C, the number of winter and spring days above 10°C and the fly activity in the preceding year) can be used in temperate regions to provide regional risk warnings (Leach et al., 2019).

P. xylostella is a migrant species whose appearance in new regions comes as a nasty surprise. A climate niche model has been developed for the moth.

The model has been used to predict the global geographic distribution of *P. xylostella*, but the moth's seasonal abundance for various locations has not been used in construction of the model. The model was also used to 'predict' historical population dynamics in Hangzhou, China, over several years, and for analysis of recent outbreaks of the species in the British Isles (Zalucki and Furlong, 2008; Zhu et al., 2018).

Climate warming has created the need to update phenological models for many pests, including *Psila rosae*, *D. radicum* and *D. antiqua*, whose peak flight and start of egg-laying are predicted with phenological models. The likelihood of *D. radicum* producing a fourth generation in the autumn in the United Kingdom is foreseen if mean annual temperatures increase by 5 or 10°C, coupled with earlier hatching of the flies from overwintering pupae (Collier et al., 1991). The warming climate can influence the flight dynamics of pests such as the codling moth during the growing season (Roşu-Mareş et al., 2020), resulting in prolonged periods of control and increased damages to crops. Samietz et al. (2013) took advantage of the improved spatial and temporal resolutions of climate model projections and modelled the phenology and generations of the codling moth. Their results also indicate that the pest's impact on apples would increase and its management would become more difficult with climate warming. Using 49 climate indices and undertaking further analyses with climate projections, Bradshaw et al. (2019) predicted that in a 2–4°C warmer world, *B. tabaci* could pose a risk to outdoor UK crops, including vegetables, in July and August. Currently, the pest occurs outdoors at the latitudes of southern France.

3 Case study: whitefly sampling, monitoring and forecasting

3.1 Two forms of plant injury by whiteflies complicate EIL and ET development

The relationship between yield reduction and plant injury by whiteflies has been elusive for a long time, since whiteflies cause economic damage in two ways: directly by depleting plants of photosynthates and indirectly by secreting honeydew. Honeydew accumulates on leaves and fruits and causes two types of harm: firstly, by favouring the growth of saprophytic fungi that block access of light to leaves and secondly, by causing aesthetic and technical harm through contamination of fruits, resulting either in loss of grade A fruits or in the need for washing them prior to sale. Honeydew production by the adult and larval stages and the effect of temperature and nitrogen fertilization on its production are known (Blua and Toscano, 1994; Costa et al., 1999; Henneberry et al., 2001; Hong and Rumei, 1993). This could in principle be used as a proxy for estimating the variable feeding intensity of immatures. In practice, measuring honeydew production is difficult and must be limited for research purposes and the EILs and ETs must be based on the proportion of contaminated fruits.

In Fig. 4, the components and their correlations needed to understand the direct and indirect effects of whiteflies on yield quantity and quality are summarized. The light green and light blue components denote variables that have been measured traditionally to study whitefly economic damage impacts on plant yield: feeding and honeydew secretion. Johnson et al. (1992) showed that the yield of field grown tomato correlated negatively with cumulative immature whitefly-days (per 1 cm leaf disk of tomato). (The whitefly days indicate the prolonged pest pressure on the physiology of plants due to feeding by both adults and immature stages.) A 5% direct yield loss, but little loss to sooty mould, occurred after 69 cumulative immature whitefly days (with a maximum of 0.7 nymphs/cm^2 in weekly samplings per plot). On the other hand, a 5% yield loss in grade A fruit caused by sooty mould contamination alone would have been reached after 298 cumulative greenhouse whitefly days (peak density = 8.3 immatures/cm^2 tomato leaflet). At that point, a total loss of 26% tomato yield would have occurred due to the combination of feeding and sooty mould contamination. No clear initial plateau in yield could be discerned; instead, yield reduction was linear throughout the sampled levels of whitefly abundance. It appears that direct yield reduction was more important than contamination of fruits with honeydew.

3.2 Sampling, monitoring and identifying of whiteflies

In an ideal world, tomato or cucumber growers can choose a monitoring protocol that depends on the size of their crop and willingness to invest in monitoring the pest. In a relatively small greenhouse, say 5000 m^2, they can use yellow sticky traps (YST) for monitoring by placing them at a distance of at least 15–20 m^2 from each other (1 trap per 200–400 m^2, roughly) so that they do not produce spatially redundant information as shown by Kim et al. (2001) and Park et al. (2011b). Besides the usual YSTs, LED-enhanced or LED-based traps that attract whiteflies have been developed and equipped with fixed cameras that take an image at selected intervals and send it to a computer screen (Stukenberg et al., 2015; Stukenberg, 2018). Counting of adult whiteflies from YSTs is being made easier by automatic counting using machine-vision-based apps (https://play.google.com/store//apps/details?id=<aidev.cocis.makerere. org.whiteflycounter &hl=fi&gl=US) (https://www.koppert.com/natutec-scout/) (McCarthy et al., 2020). A statistical model, based on machine-vision data, for distinguishing *T. vaporariorum* and *B. tabaci* adults from each other in traps has also been developed (Moerkens et al., 2019). Even immature

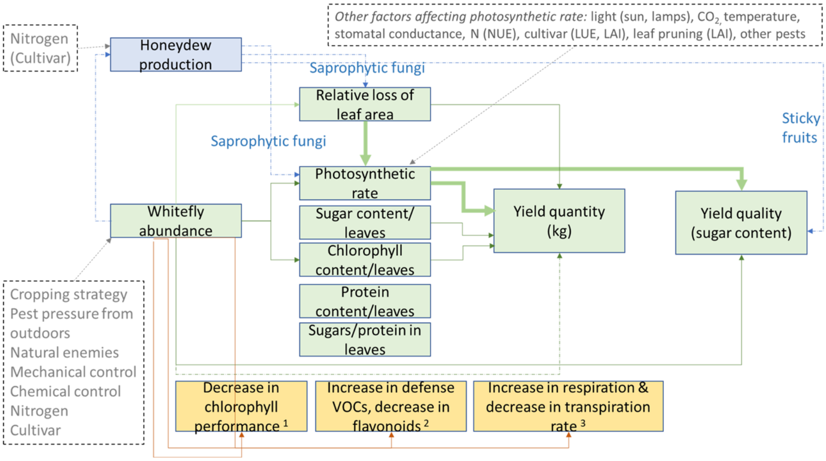


Figure 4 Factors needed to understand plant injury and economic damage caused to plants by *Trialeurodes vaporariorum*. Data for cucumber (green boxes) (Rumei and Liying, 1991) were used to indicate the relative strength of correlations between, plant growth indices, yield quantity and quality and abundance of *T. vaporariorum*. Thick green line: correlation significant at 0.01. Thin green line: correlation significant at 0.05. Dashed thin line: correlation almost significant. The correlations between honeydew production with growth indices are not based on empirical results, just sketched to show the relationships. The orange boxes give the most recent research targets for the impacts of whitefly on plants, and eventually yield. Their direct correlations with variables in the green and blue boxes are not known, but all correlate significantly with whitefly density. References: 1 (Cai et al., 2016; Chen et al., 2011) for tomato, 2 (Darshanee et al., 2017; Su et al., 2018) for tomato, 3 (Shannag and Freihat, 2009) for cucumber.

stages on leaves can nowadays be distinguished from each other and counted automatically, but such phenotyping is currently cost-effective and practical only for research purposes used in the laboratory (Anonymous, 2021).

From the traps, the grower monitors both the pest and a predatory bug *M. pygmaeus* and can conclude from their relative counts whether biocontrol by the predator is going well or not (Böckmann and Meyhöfer, 2017; Moerkens et al., 2020). Based on trap catches of the parasitoid *Encarsia formosa*, she can also conclude whether parasitism is going on well: six or more individuals per trap indicates the parasitoid is keeping the pest in control (Böckmann et al., 2014). Should the grower want to check the parasitization rate of puparia on the leaves, she can use the threshold of 80% black, parasitized pupae for concluding that the whitefly situation is in control (van Roermund et al., 1997). And if the grower is well updated, she knows that she must place Encarsia cards so that there is no more than an 8 m distance from one point to another. Otherwise there will be areas that parasitoids do not cover (Pérez et al., 2011).

3.3 Possibilities of physiological EILs

To succeed in biological control, the grower must have started control measures as soon as she observed the first whiteflies in the crop. The whiteflies reduce the chlorophyll content of leaves, the performance of the remaining chlorophyll gets poorer than normal and the stomatal conductance also decreases; these negative consequences take place in both tomato (Buntin et al., 1993) and cucumber (Rumei and Liying, 1991; Shannag and Freihat, 2009). Provided that there were no more than five to six adult whiteflies per plant in the beginning of the infestation (an EIL in greenhouse cucumber where the economic damage will develop into significant yield reductions in 2–3 months in the absence of control measures, as shown by Jeon et al. (2009)), such reductions in plant performance will not be reflected in the yield immediately. In cucumber, 20% of chlorophyll content of leaves can decrease before it results in yield decrease (Rumei and Liying, 1991); at this point, sooty moulds due to honeydew secretion are not present yet, so yield reduction is directly from the sucking action by whiteflies. So there is time to act after detecting the whiteflies but the length of time depends on the initial level of infestation and on stages of whiteflies of the initial infestation (Rumei and Liying, 1991).

The extent to which stomatal conductance and chlorophyll content and performance are reduced and transpiration is increased depends on how plants are fertilized, how much light they receive, how high fruit load they have and what other biotic and abiotic stressors are affecting them. The physiological direct yield response varies depending on environmental conditions, but this correlation remains understudied. Current portable phenotyping instruments such as fluorometers for measuring chlorophyll and secondary metabolites (Groher, 2019), chlorophyll meters (Chrysargyris et al., 2020; Vesali et al., 2017), porometers for measuring stomatal conductance (Buntin et al., 1993) and Fv/Fm-meters for measuring the maximum quantum efficiency of the plants' photosystem (Poudyal et al., 2019) can be used to determine physiological changes in crop plants. The data can be used for determining physiological EILs. Big Data approaches should help in revealing the correlations between such physiological responses and environmental factors.

3.4 Simultaneous mass trapping and monitoring with sticky traps: consequences to ETs?

In year-round tomato and cucumber crops in Finland at the beginning of the 2010s, nominal thresholds for initiating occasional treatments with selective pesticides were based on whitefly catches with sticky traps. Relatively few growers monitored whitefly dynamics with YSTs at that time. Following a collaborative project in 2010–12 (Vänninen et al., 2015), the use of sticky traps for monitoring increased and nominal thresholds developed with input from growers and advisors were taken up more widely. At the same time, however, large yellow sticky bands for mass trapping gained popularity, as an approach to improve whitefly management in year-round crops where biocontrol does not work as reliably as in summer crops. This has created a new situation: the small YSTs used for monitoring seem to catch fewer whiteflies nowadays, as the large yellow glue bands hung above every row of the crop seemingly compete with the small traps by attracting more whiteflies.

At the moment, there are no fixed thresholds and decision-making is based on the experience of growers and advisors, either in counting/observing adults from leaves in plant tops or monitoring whiteflies with YST or a combination of these approaches. Decision-making based on experience can work well but seems to be insufficient in years when whitefly pressure is high due to outdoor weather conditions that promote whitefly reproduction in wild plants near greenhouses; subsequently, the pest pressure in the autumn from outdoors is high when winter crops of tomato and cucumber are planted in the greenhouses and attract whiteflies from outdoors when the weather gets colder. The large yellow glue bands can also influence the spatial distribution of whiteflies in the crops. No formal studies on whitefly distribution in these cropping systems have been made so far but are now being conducted.

3.5 New approaches to whitefly monitoring

Spotting and locating whitefly hot spots is one goal of monitoring. This can be achieved using information on spatial distribution of whiteflies to cover the greenhouse area with appropriate placement of YSTs, as described above, or by plant sampling plans. Plant sampling is not a common procedure in greenhouse tomato and cucumber except for observing adults in tops of plants when working on the plants daily. Growers develop nominal thresholds based on experience of seeing adults on the top leaves and combine this information with YST counts, if the latter are used. Formal sampling plans for adult and immature counts have been developed for outdoor tomato crops. Sequential sampling plans with fixed precision for *B. tabaci* immatures were shown to reduce the number of needed leaf samples by 60–70% compared to conventional sampling plans based on fixed sample sizes (Gusmão et al., 2006, 2005) – a considerable reduction in time and labour for sampling. Better coverage of microclimate monitoring would help in recognizing risk zones for whitefly hot spots, as shown below.

For very large greenhouses where even YST monitoring is impractical, robotic platforms based on optochemical techniques are already available (https://www.ecoation.com). They scan plant rows for pests and fruit ripeness automatically but take in also human observations in digital form. The detection can be based on multispectral or hyperspectral imaging, but also on detection of volatile organic compounds emitted by infested plants – no information is available on this. A detection process that covers all plant rows makes the need for knowledge on spatial distribution of the pest obsolete and helps detect hotspots. The platform's AI system is so designed that it can correlate pest pressure and microclimatic conditions (temperature, humidity, light intensity, air currents) and therefore can help identify zones of high pest risk. The system also does future projections to forecast pest pressures within the coming week which helps to order the right amounts of biocontrol agents. Sophisticated AI-based statistical algorithms based on data that is accumulated continuously are doing the job that is too complex for humans alone (Ecoation, n.d.).

3.6 Simulation of whitefly population dynamics

Many mathematical simulation models have been created to map the responses of whiteflies to temperature. They include both linear and non-linear phenological models, with or without stochasticity, for development times or rates based on temperature (and host plant) (Chandi et al., 2021; Drost et al., 1998; Gamarra et al., 2020; Muñiz and Nombela, 2001; Nava-Camberos et al., 2001; Wang and Tsai, 1996). In most models air temperature is used, but leaf temperature has been shown to explain development time better (Park et al., 2011a). Life-table and population dynamic models for whiteflies include differential equations, matrix models, dimension-changeable matrix models and box car train models (Giessen et al., 1995; Hulspas-Jordaan and van Lenteren, 1989; van Roermund and van Lenteren, 1992; Yeow and Becker, 2018).

The interaction of whiteflies with their important natural enemy *Encarsia formosa* has been modelled by several researchers (e.g. Hulspas-Jordaan and van Lenteren, 1989; Yano et al., 1989). Rodríguez (2016) also included the whiteflies' interaction with powdery mildew that often occurs on tomato leaves together with whiteflies and can influence both the pest and its natural enemies. Rincon et al. (2015) produced an algorithm to simulate the effect of within-plant heterogeneity on whitefly–predator dynamics based on explicit prey spatial distributions. Such models can be used to scale-up functional responses of natural enemies. Giessen et al. (1995) explored the effects of antibiotic resistance of tomato plants on whitefly population development with a deterministic model. Moerkens et al. (2020) used simple statistical modelling based on whitefly and *Macrolophus* counts in YSTs to predict the success level of biocontrol. With the development of wireless sensors or moving robotic AI-platforms that measure microclimate on the go and accumulate data on pest densities at the same time, the predictive use of forecasting models is being integrated into whitefly management in decision support systems.

4 Conclusion

Pest monitoring in horticulture is developing technologically to reduce time and labour needed for sampling and to produce more accurate pest predictions. New ways of detecting pests based on selective e-traps, e-noses, cameras and acoustic signatures are already in use or emerging. Remote sensing of pests requires the development of new economic injury levels and ETs. The relative importance of mechanistic and statistical models is changing due to AI-technologies and Big Data. The use of Big Data will force researchers to collect, use and value data differently than before. The incorporation of natural enemies in ETs will take place gradually and require researchers to acquire modelling skills. Research for advancing monitoring and forecasting also must include the socioeconomic factors that determine whether new technologies will be implemented by farmers. Developing trustworthy sampling plans and forecasting models, and validating and implementing them in collaboration with stakeholders, remains important.

5 Future trends in research

The new, high-technological approaches to data collection and management appear very prominently in the research literature of pest management nowadays. The feasibility of these new technologies in annual and perennial horticultural crops of different sizes is an issue that needs to be considered as one of the research targets. Remote-sensing techniques require new ETs to be developed. Criteria can be developed in advance concerning the feasibility of new solutions for specific purposes as exemplified by the study of Cock et al. (2016) evaluating the usefulness of remote sensing for monitoring key agricultural pests. Feasibility evaluations should not, however, restrict empirical research too much, as practice often produces serendipitous new information and seeds for innovations that cannot be produced only by theory.

Remote sensing can indicate the occurrence of a pest in the crop, without having to pay attention to the pest's spatial distribution when collecting data. But can remote sensors tell also on the abundance of all pests or the abundance of natural enemies that influence the future trajectory of the pest population? Hardly. Phenological models will use increasingly site-specific data and become very accurate, but their output does not tell whether the pest really occurs at a specific site or how many pests there will be. Possibilities of using mobile phones for implementing accurate enough sequential sampling plans that are also user-friendly and not costly to use deserve research investments. The uncertainty of information is an issue that influences growers' willingness to follow ET recommendations. Does their willingness to rely on fixed ETs change if they obtain reliable evidence on how certain the ETs are or should ETs see as learning tools that help growers to adjust their behaviour regarding intervention decisions? Are ETs that take into account the level of risk aversion of growers more readily accepted than fixed one-option ETs? If ETs are probabilistic, does this increase or decrease growers' willingness to apply them? How to address the gap between the theory and practice of sampling and monitoring? Sampling plans are worth nothing if they serve only the CV of researchers and publication lists. Fitting them into the agenda and activities of stakeholders is the ultimate goal and must be included in research on sampling, monitoring and forecasting.

While digitalization is gaining a foothold in horticulture, the importance of biology, ecology and physiology of organisms is actually being accentuated with the advancement of new technologies. The Big Data collected must represent relevant life stages and events in the pests' life cycles. A similar requirement comes from the inclusion of natural enemies in ETs. Biological research is needed also to couple the knowledge concerning the pest, its natural enemies and the crop plant with each other for modelling purposes and for the timing of control actions such as push–pull technologies, use of trap crops or spatial and temporal performance of biocontrol agents. Sampling methods and decision thresholds for natural enemies will gradually become more important research targets. Studies on tangible quantified impacts of natural enemies associated with ETs are still scarce and must be incorporated in bioeconomic models. Improvements of phenology models of both pests and natural enemies are still needed to make the outputs more precise and to improve region- or site-specificity of outputs. Climate change is also contributing to this research need, as updated data are required on pest and natural enemy biology and interactions (Collier et al., 2020).

Sharing pest observations among growers and researchers with the help of current IT solutions should be encouraged by research to show its benefits for collecting Big Data and for being able to adjust sampling and management decisions with changing contexts of farming. Field-level precision farming decisions can then be combined with knowledge obtained from wider spatial and temporal scales that, depending on the pest species, can influence local pest conditions and decision-making. Using Big data successfully requires collaboration between theory (in the natural sciences) and practice (farmers, IPM researchers, advisors, AI specialists) so that we understand the type of data that is valuable and what are not.

Research on the application of automated identification and more selective trapping of insects will continue. New sensory domains (olfaction, acoustics) are already included in research agendas concerning insect and mite responses to their environment and the application of sensors to identify insects. For example, could wingbeat frequencies be used to distinguish species of *Delia* when they enter semi-selective traps? No information exists as yet. It seems that studies on the chemical ecology of several pest species are being revived now that research methods have become more sophisticated, our understanding of insect olfaction has increased and successful examples of kairomone traps are available as examples. New approaches must be compared with existing sampling methods in terms of efficacy and cost, to choose the best solution from the practical point of view.

6 Where to look for further information

6.1 Further reading

- A concise overview of sampling principles and practices in lecture form: Barbour, J. Sampling Insect Populations for Pest Management: http://pnwpestalert.net/uploads/meetings/BarbourIPMsampling.pdf.
- Binns, M. R., Nyrop, J. P., van der Werf, W. and Wopke, W. 2000. *Sampling and Monitoring in Crop Protection: The Theoretical Basis for Developing Practical Decision Guides*. CABI.
- Higley, L. G. and Pedigo, L. P. 1996. *Economic Thresholds for Integrated Pest Management*. University of Nebraska Press.
- Koul, O. and Cuperus, G. W. (Eds.). 2007. *Ecologically Based Integrated Pest Management*. CABI.
- Pedigo, L. P. and Buntin, G. D. 1993. *Handbook of Sampling Methods for Arthropods in Agriculture*. CRC Press.
- Remote sensing for insect pests – reviews and case studies (Potamitis et al., 2017; Roosjen et al., 2020; Suckling et al., 2020; Zhang et al., 2019).
- Review on the role of kairomones in IPM: (Murali-Baskaran et al., 2018).
- A review of sampling and monitoring methods for beneficial arthropods in agroecosystems (McCravy, 2018).
- Local, regional and global performance of models and effects on resource use of research: how to direct efforts and resources, also in the context of current IPM programs and monitoring and forecasting as one of its principles (Berlin et al., 2018).
- Big Data and IPM: Data types and collection (Zaza et al., 2018); Data processing (Pratheepa and Antony, 2018); Data valuation (Demirel and Kumral, 2021; Weersink et al., 2018).
- Integrated Pest Management Pheromones Market Size, Share & Trends Analysis Report (2020–2027): https://www.grandviewresearch.com/industry-analysis/ipm-pheromones.

6.2 Examples of companies offering tools for automated monitoring and identification of pests and platforms for documentation of scouting and sensor data

- https://metos.at/iscout/.
- https://www.trapview.com/v2/en/.
- https://www.ecoation.com/.
- https://arisbv.nl/en/vision-for-phenotyping/ornamental-crops-2/phenotyping-products/cirillo.
- https://www.botany.nl/en/cirillo.
- https://www.koppert.com/natutec-scout/.
- https://www.letsgrow.com.
- https://www.30mhz.com/products/platform/.

7 References

Abd El-Ghany, N. M., Abd El-Aziz, S. E. and Marei, S. S. 2020. A review: Application of remote sensing as a promising strategy for insect pests and diseases management. *Environ. Sci. Pollut. Res. Int.* 27(27), 33503–33515. https://doi.org/10.1007/s11356-020-09517-2.

Adams, C. G. 2017. Maximizing information yield from pheromone-baited monitoring traps: Estimating plume reach, trapping radius, and absolute density of Cydia pomonella (Lepidoptera: Tortricidae) in Michigan apple. *J. Econ. Entomol.* 110(2), 305–318.

Agnello, A. M., Kovach, J., Nyrop, J. P., Reissig, W. H., Breth, D. I. and Wilcox, W. F. 1994. Extension and evaluation of a simplified monitoring program in New York Apples. *Am. Entomol.* 40(1), 37–49. https://doi.org/10.1093/ae/40.1.37.

Alatawi, F. J., Opit, G. P., Margolies, D. C. and Nechols, J. R. 2005. Within-plant distribution of twospotted spider mites (Acari: Tetranychidae) on impatiens: Development of a presence–absence sampling plan. *J. Econ. Entomol.* 98(3), 1040–1047. https://doi.org/10.1603/0022-0493-98.3.1040.

Amarasekare, K. G. and Shearer, P. W. 2013. Laboratory bioassays to estimate the lethal and sublethal effects of various insecticides and fungicides on Deraeocoris brevis (Hemiptera: Miridae). *J. Econ. Entomol.* 106(2), 776–785. https://doi.org/10.1603/EC12432.

Anonymous 2020. Apple IPM sampling charts. Cornell University. Available at: https://nysipm.cornell.edu/sites/nysipm.cornell.edu/files/shared/documents/apple-IPM-sampling-charts.pdf.

Anonymous 2021. Botany en Aris richten joint venture PhenoVerius op voor insecttellingen op planten. *Groenten Nieuws*.

Baker, R. E., Peña, J. M., Jayamohan, J. and Jérusalem, A. 2018. Mechanistic models versus machine learning, a fight worth fighting for the biological community? *Biol. Lett.* 14(5), 29769297. https://doi.org/10.1098/rsbl.2017.0660.

Bannerman, J. A., Costamagna, A. C., McCornack, B. P. and Ragsdale, D. W. 2015. Comparison of relative bias, precision, and efficiency of sampling methods for natural enemies of soybean aphid (Hemiptera: Aphididae). *J. Econ. Entomol.* 108(3), 1381–1397. https://doi.org/10.1093/jee/tov009.

Barbedo, J. G. A. 2019. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. *Drones*. 3(2), 40. https://doi.org/10.3390/drones3020040.

Baroffio, C. A., Sigsgaard, L., Ahrenfeldt, E. J., Borg-Karlson, A.-K., Bruun, S. A., Cross, J. V., Fountain, M. T., Hall, D., Mozuraitis, R., Ralle, B., Trandem, N. and Wibe, A. 2018. Combining plant volatiles and pheromones to catch two insect pests in the same trap: Examples from two berry crops. *Crop Prot*. 109, 1–8.

Barros, P. P. S., Schutze, I. X., Iost Filho, F. H., Yamamoto, P. T., Fiorio, P. R. and Demattê, J. A. M. 2021. Monitoring Bemisia tabaci (Gennadius) (Hemiptera: Aleyrodidae) infestation in soybean by proximal sensing. *Insects*. 12(1), 47. https://doi.org/10.3390/insects12010047.

Bažok, R., Ceranić-Sertić, M., Barčić, J. I., Borošić, J., Kozina, A., Kos, T., Lemić, D. and Čačija, M. 2012. Seasonal flight, optimal timing and efficacy of selected insecticides for cabbage maggot (Delia radicum L., Diptera: Anthomyiidae) control. *Insects*. 3(4), 1001–1027. https://doi.org/10.3390/insects3041001.

Bengtsson, M., Jaastad, G., Knudsen, G., Kobro, S., Bäckman, A.-C., Pettersson, E. and Witzgall, P. 2006. Plant volatiles mediate attraction to host and non-host plant in apple fruit moth, Argyresthia conjugella. *Entomol. Exp. Appl.* 118(1), 77–85. https://doi.org/10.1111/j.1570-7458.2006.00359.x.

Benjamin, E. O. and Wesseler, J. H. H. 2016. Social science perspectives on the bio-economy. A socioeconomic analysis of biocontrol in integrated pest management: A review of the effects of uncertainty, irreversibility and flexibility. *NJAS Wagening. J. Life. Sci*. 77, 53–60. https://doi.org/10.1016/j.njas.2016.03.002.

Berlin, A., Källström, H. N., Lindgren, A. and Olson, Å. 2018. Scientific evidence for sustainable plant disease protection strategies for the main arable crops in Sweden. A systematic map protocol. *Environ. Evid.* 7(1), 31. https://doi.org/10.1186/s13750-018-0141-3.

Binns, M. R. and Nyrop, J. P. 1992. Sampling insect populations for the purpose of IPM decision making. *Annu. Rev. Entomol.* 37(1), 427–453. https://doi.org/10.1146/annurev.en.37.010192.002235.

Binns, M. R., Nyrop, J. P. and Van Der Werf, W. 1996. Monitoring pest abundance by cascading density classification. *Am. Entomol.* 42(2), 113–121. https://doi.org/10.1093/ae/42.2.113.

Binns, M. R., Nyrop, J. P., van der Werf, W. and Werf, W. 2000. *Sampling and Monitoring in Crop Protection: The Theoretical Basis for Developing Practical Decision Guides*. Wallingford, UK; New York: CABI Publishing.

Biron, D. G., Coderre, D., Boivin, G., Brunel, E. and Nénon, J. P. 2002. Genetic variability and expression of phenological and morphological differences in populations of Delia radicum (Diptera: Anthomyiidae). *Can. Entomol.* 134(3), 311–327. https://doi.org/10.4039/Ent134311-3.

Bleeker, P. M., Diergaarde, P. J., Ament, K., Schütz, S., Johne, B., Dijkink, J., Hiemstra, H., de Gelder, R., de Both, M. T. J., Sabelis, M. W., Haring, M. A. and Schuurink, R. C. 2011. Tomato-produced 7-epizingiberene and R-curcumene act as repellents to whiteflies. *Phytochemistry* 72(1), 68–73. https://doi.org/10.1016/j.phytochem.2010.10.014.

Bleeker, P. M., Mirabella, R., Diergaarde, P. J., VanDoorn, A., Tissier, A., Kant, M. R., Prins, M., de Vos, M., Haring, M. A. and Schuurink, R. C. 2012. Improved herbivore resistance in cultivated tomato with the sesquiterpene biosynthetic pathway from a wild relative.

Proc. Natl. Acad. Sci. USA 109(49), 20124–20129. https://doi.org/10.1073/pnas.1208756109.

Bligaard, J. 1999. Damage thresholds for cabbage root fly [*Delia radicum* (L.)] in cauliflower assessed from pot experiments. *Acta Agric. Scand. B* 49(1), 57–64. https://doi.org/10.1080/09064719950135713.

Blua, M. J. and Toscano, N. C. 1994. Bemisia argentifolii (Homoptera: Aleyrodidae) development and honeydew production as a function of cotton nitrogen status. *Environ. Entomol.* 23(2), 316–321. https://doi.org/10.1093/ee/23.2.316.

Böckmann, E., Hommes, M. and Meyhöfer, R. 2014. Yellow traps reloaded: What is the benefit for decision making in practice? *J. Pest. Sci.* 88, 439–449. https://doi.org/10.1007/s10340-014-0601-7.

Böckmann, E. and Meyhöfer, R. 2017. Sticky trap monitoring of a pest–predator system in glasshouse tomato crops: Are available trap colours sufficient? *J. Appl. Entomol.* 141(5), 339–351. https://doi.org/10.1111/jen.12338.

Bradshaw, C. D., Hemming, D., Baker, R., Everatt, M., Eyre, D. and Korycinska, A. 2019. A novel approach for exploring climatic factors limiting current pest distributions: A case study of Bemisia tabaci in north-west Europe and assessment of potential future establishment in the United Kingdom under climate change. *PLoS ONE.* 14(8), e0221057. https://doi.org/10.1371/journal.pone.0221057.

Buntin, D. G., Gilbertz, D. A. and Oetting, R. D. 1993. Chlorophyll loss and gas exchange in tomato leaves after feeding injury by Bemisia tabaci (Homoptera: Aleyrodidae). *J. Econ. Entomol.* 86(2), 517–522. https://doi.org/10.1093/jee/86.2.517.

Cai, C., Xu, Y. and Cui, X. 2016. Physiological characteristics of different resistant tomato varieties in response to B-type Bemisia tabaci stress. *Chin. Agric. Sci.* 49, 2524–2533.

Cardim Ferreira Lima, M., Damascena de Almeida Leandro, M. E., Valero, C., Pereira Coronel, L. C. and Gonçalves Bazzo, C. O. 2020. Automatic detection and monitoring of insect pests—A review. *Agriculture* 10(5), 161. https://doi.org/10.3390/agriculture10050161.

Castle, S. and Naranjo, S. E. 2009. Sampling plans, selective insecticides and sustainability: The case for IPM as 'informed pest management'. *Pest Manag. Sci.* 65(12), 1321–1328. https://doi.org/10.1002/ps.1857.

Cha, D. H., Hesler, S. P., Wallingford, A. K., Zaman, F., Jentsch, P., Nyrop, J. and Loeb, G. M. 2018. Comparison of commercial lures and food baits for early detection of fruit infestation risk by Drosophila suzukii (Diptera: Drosophilidae). *J. Econ. Entomol.* 111(2), 645–652. https://doi.org/10.1093/jee/tox369.

Chandi, R. S., Kataria, S. K. and Fand, B. B. 2021. Effect of temperature on biological parameters of cotton whitefly, Bemisia tabaci (Gennadius) (Hemiptera: Aleyrodidae). *Int. J. Trop. Insect Sci.* 41(2), 1823–1833. https://doi.org/10.1007/s42690-020-00397-0.

Chen, M. S., Wheeler, S., Davis, H., Jeff Whitworth, R. J., Knutson, A., Giles, K. L., Royer, T. A. and Skinner, M. 2014. Molecular markers for species identification of Hessian fly males caught on sticky pheromone traps. *J. Econ. Entomol.* 107(3), 1110–1117. https://doi.org/10.1603/EC13384.

Chen, Y., Cui, X., Cai, C. and Cao, F. 2011. Effect of Bemisia tabaci (Gennadius) B-biotype on photosynthetic characteristics and activity of defense enzyme in different varieties of tomato. *Sci. Agric. Sin.* 44, 3547–3556.

Chow, Y. S., Lin, Y. M. and Hsu, C. L. 1977. Sex pheromone of the diamondback moth (Lepidoptera: Plutellidae). *Bull. Inst. Zool. Acad. Sin.* 16, 99–105.

Chrysargyris, A., Charalambous, S., Xylia, P., Litskas, V., Stavrinides, M. and Tzortzakis, N. 2020. Assessing the biostimulant effects of a novel plant-based formulation on tomato crop. *Sustainability.* 12(20), 8432. https://doi.org/10.3390/su12208432.

Chua, T. H. and Lim, B. H. 1979. Distribution pattern of diamondback moth, *plutella xylostella* (L.) (Lepidoptera: Plutellidae) on choy-sum plants. *Z. Angew. Entomol.* 88(1–5), 170–175. https://doi.org/10.1111/j.1439-0418.1979.tb02492.x.

Cloonan, K. R., Abraham, J., Angeli, S., Syed, Z. and Rodriguez-Saona, C. 2018. Advances in the chemical ecology of the spotted wing Drosophila (Drosophila suzukii) and its applications. *J. Chem. Ecol.* 44(10), 922–939. https://doi.org/10.1007/s10886-018-1000-y.

Cloonan, K. R., Hernández-Cumplido, J., De Sousa, A. L. V., Ramalho, D. G., Burrack, H. J., Della Rosa, L., Diepenbrock, L. M., Ballman, E., Drummond, F. A., Gut, L. J., Hesler, S., Isaacs, R., Leach, H., Loeb, G. M., Nielsen, A. L., Nitzsche, P., Park, K. R., Syed, Z., Van Timmeren, S., Wallingford, A. K., Walton, V. M. and Rodriguez-Saona, C. 2019. Laboratory and field evaluation of host-related foraging odor-cue combinations to attract Drosophila suzukii (Diptera: Drosophilidae). *J. Econ. Entomol.* 112(6), 2850–2860. https://doi.org/10.1093/jee/toz224.

Cock, M. J. W., Rui, T., Zhi, L., HuanHuan, W., McGillivray, L. A., Thomas, S. E., Cameron, K. H. and Feng, Z. 2016. The main agricultural insect and disease pests of China and implications for the use of remote sensing for their management. *CAB Rev*. 11, 14.

Collier, R., Mazzi, D., Folkedal Schjøll, A., Schorpp, Q., Thöming, G., Johansen, T. J., Meadow, R., Meyling, N. V., Cortesero, A. M., Vogler, U., Gaffney, M. T. and Hommes, M. 2020. The potential for decision support tools to improve the management of root-feeding fly pests of vegetables in western Europe. *Insects* 11(6), 369. https://doi.org/10.3390/insects11060369.

Collier, R. H., Finch, S., Phelps, K. and Thompson, A. R. 1991. Possible impact of global warming on cabbage root fly (Delia radicum) activity in the UK. *Ann. Appl. Biol.* 118(2), 261–271. https://doi.org/10.1111/j.1744-7348.1991.tb05627.x.

Costa, H. S., Toscano, N. C., Hendrix, D. L. and Henneberry, T. J. 1999. Patterns of honeydew droplet production by nymphal stages of Bemisia argentifolii (Homoptera: Aleyrodidae) and relative composition of honeydew sugars. *J. Entomol. Sci.* 34(3), 305–313. https://doi.org/10.18474/0749-8004-34.3.305.

Cross, J. V., Hall, D. R., Innocenzi, P. J., Hesketh, H., N Jay, C. and Burgess, C. M. 2006a. Exploiting the aggregation pheromone of strawberry blossom weevil Anthonomus rubi (Coleoptera: Curculionidae): Part 2. Pest monitoring and control. *Crop Prot.* 25(2), 155–166. https://doi.org/10.1016/j.cropro.2005.04.004.

Cross, J. V., Hesketh, H., Jay, C. N., Hall, D. R., Innocenzi, P. J., Farman, D. I. and Burgess, C. M. 2006b. Exploiting the aggregation pheromone of strawberry blossom weevil Anthonomus rubi Herbst (Coleoptera: Curculionidae): Part 1. Development of lure and trap. *Crop Prot.* 25(2), 144–154. https://doi.org/10.1016/j.cropro.2005.04.002.

Cui, S., Ling, P., Zhu, H. and Keener, H. M. 2018. Plant pest detection using an artificial nose system: A review. *Sensors (Basel).* 18(2), 378. https://doi.org/10.3390/s18020378.

Dai, J., Deng, J. and Du, J. 2008. Development of bisexual attractants for diamondback moth, *Plutella xylostella* (Lepidoptera: Plutellidae) based on sex pheromone and host volatiles. *Appl. Entomol. Zool.* 43(4), 631–638. https://doi.org/10.1303/aez.2008.631.

Dalton, D. T., Walton, V. M., Shearer, P. W., Walsh, D. B., Caprile, J. and Isaacs, R. 2011. Laboratory survival of Drosophila suzukii under simulated winter conditions of the

Pacific Northwest and seasonal field trapping in five primary regions of small and stone fruit production in the United States. *Pest. Manag. Sci.* 67(11), 1368–1374. https://doi.org/10.1002/ps.2280.

Damos, P. 2014. Stochastic modeling of economic injury levels with respect to yearly trends in price commodity. *J. Insect Sci.* 14, 59. https://doi.org/10.1093/jis/14.1.59.

Damos, P. and Soulopoulou, P. 2019. Stage-specific probabilistic phenology model of Cydia pomonella (Lepidoptera: Tortricidae) using laboratory maximum likelihood parameter estimates. *J. Appl. Entomol.* 143(3), 250–261. https://doi.org/10.1111/jen.12589.

Darshanee, H. L. C., Ren, H., Ahmed, N., Zhang, Z. F., Liu, Y. H. and Liu, T. X. 2017. Volatile-mediated attraction of greenhouse whitefly Trialeurodes vaporariorum to tomato and eggplant. *Front. Plant Sci.* 8, 1285. https://doi.org/10.3389/fpls.2017.01285.

Degen, T., Buser, H.-R. and Städler, E. 1999. Patterns of oviposition stimulants for carrot fly in leaves of various host plants. *J. Chem. Ecol.* 25(1), 67–87. https://doi.org/10.1023/A:1020837116467.

Demirel, M. and Kumral, N. A. 2021. Artificial intelligence in integrated pest management. In: *Artificial Intelligence and IoT-Based Technologies for Sustainable Farming and Smart Agriculture*. Hershey, PA: IGI Global, 289–313.

Donatelli, M., Magarey, R. D., Bregaglio, S., Willocquet, L., Whish, J. P. M. and Savary, S. 2017. Modelling the impacts of pests and diseases on agricultural systems. *Agric. Syst.* 155, 213–224. https://doi.org/10.1016/j.agsy.2017.01.019.

Dreves, A. J. 2006. Phenology and monitoring of the cabbage maggot, *Delia radicum* (L.), in brassica root crops. PhD Thesis. Oregon State University, Corvallis, OR.

Drost, Y. C., van Lenteren, J. C. and van Roermund, H. J. W. 1998. Life-history parameters of different biotypes of Bemisia tabaci (Hemiptera: Aleyrodidae) in relation to temperature and host plant: A selective review. *Bull. Entomol. Res.* 88(3), 219–230. https://doi.org/10.1017/S0007485300025840.

Ecoation n.d. *Integrated Pest Management. How the Ecoation OKO Platform Uses Sensors and AI to Optimize IPM Programs and Reduce Treatment Cost in Greenhouses*. Available at: https://www.ecoation.com/_files/ugd/0a894f_a83293fa199c4f60a71254187a0b7f4c.pdf.

Edland, T. 1974. The rowan-berry moth (Argyresthia conjugella Zell.). Prognosis of attack on apple. Methods and results. A preliminary report. *Garneryrket.* 64, 524–532.

Estrada-Hernández, M. G., Valenzuela-Soto, J. H., Ibarra-Laclette, E. and Délano-Frier, J. P. 2009. Differential gene expression in whitefly Bemisia tabaci-infested tomato (*Solanum lycopersicum*) plants at progressing developmental stages of the insect's life cycle. *Physiol. Plant.* 137(1), 44–60. https://doi.org/10.1111/j.1399-3054.2009.01260.x.

Evans, K. J., Terhorst, A. and Kang, B. H. 2017. From data to decisions: Helping crop producers build their actionable knowledge. *Crit. Rev. Plant Sci.* 36(2), 71–88. https://doi.org/10.1080/07352689.2017.1336047.

Evenden, M. L. and Gries, R. 2010. Assessment of commercially available pheromone lures for monitoring diamondback moth (Lepidoptera: Plutellidae) in canola. *J. Econ. Entomol.* 103(3), 654–661. https://doi.org/10.1603/EC09339.

Fenu, G. and Malloci, F. M. 2021. Forecasting plant and crop disease: An explorative study on current algorithms. *Big Data Cogn. Comput.* 5(1), 2. https://doi.org/10.3390/bdcc5010002.

Finch, S., Collier, R. H. and Phelps, K. 1996. A review of work done to forecast pest insect attacks in UK horticultural crops. *Crop. Prot.* 15(4), 353–357. https://doi.org/10.1016/0261-2194(95)00135-2.

Finch, S. and Skinner, G. 1982. Trapping cabbage root flies in traps baited with plant extracts and with natural and synthetic isothiocyanates. *Entomol. Exp. Appl.* 31(2–3), 133–139. https://doi.org/10.1111/j.1570-7458.1982.tb03124.x.

Finch, S., Skinner, G. and Freeman, G. H. 1975. The distribution and analysis of cabbage root fly egg populations. *Ann. Appl. Biol.* 79(1), 1–18. https://doi.org/10.1111/j.1744-7348.1975.tb01516.x.

Finch, S., Skinner, G. and Freeman, G. H. 1978. Distribution and analysis of cabbage root fly pupal populations. *Ann. Appl. Biol.* 88(3), 351–356. https://doi.org/10.1111/j.1744-7348.1978.tb00724.x.

Fountain, M. T., Baroffio, C., Borg-Karlson, A.-K., Brain, P., Cross, J. V., Farman, D. I., Hall, D. R., Ralle, B., Rendina, P., Richoz, P., Sigsgaard, L., Storberget, S., Trandem, N. and Wibe, A. 2017. Design and deployment of semiochemical traps for capturing Anthonomus rubi Herbst (Coleoptera: Curculionidae) and Lygus rugulipennis Poppius (Hetereoptera: Miridae) in soft fruit crops. *Crop. Prot.* 99, 1–9. https://doi.org/10.1016/j.cropro.2017.05.001.

Franklin, J. 2010. *Mapping Species Distributions: Spatial Inference and Prediction*. Cambridge: Cambridge University Press.

Frewin, A. J., Renkema, J., Fraser, H. and Hallett, R. H. 2017. Evaluation of attractants for monitoring Drosophila suzukii (Diptera: Drosophilidae). *J. Econ. Entomol.* 110(3), 1156–1163. https://doi.org/10.1093/jee/tox081.

Frey, J. E. and Frey, B. 1995. Molecular identification of six species of scale insects (Quadraspidiotus sp.) by RAPD-PCR: Assessing the field-specificity of pheromone traps. *Mol. Ecol.* 4(6), 777–780. https://doi.org/10.1111/j.1365-294X.1995.tb00279.x.

Gamarra, H., Sporleder, M., Carhuapoma, P., Kroschel, J. and Kreuze, J. 2020. A temperature-dependent phenology model for the greenhouse whitefly Trialeurodes vaporariorum (Hemiptera: Aleyrodidae). *Virus. Res.* 289, 198107. https://doi.org/10.1016/j.virusres.2020.198107.

Gent, D. H., De Wolf, E. and Pethybridge, S. J. 2011. Perceptions of risk, risk aversion, and barriers to adoption of decision support systems and integrated pest management: An introduction. *Phytopathology* 101(6), 640–643. https://doi.org/10.1094/PHYTO-04-10-0124.

Giessen, W. A. V., Mollema, C. and Elsey, K. D. 1995. Design and use of a simulation model to evaluate germplasm for antibiotic resistance to the greenhouse whitefly (Trialeurodes vaporariorum) and the sweetpotato whitefly (Bemisia tabaci). *Entomol. Exp. Appl.* 76(3), 271–286. https://doi.org/10.1111/j.1570-7458.1995.tb01971.x.

Giles, K. L., McCornack, B. P., Royer, T. A. and Elliott, N. C. 2017. Incorporating biological control into IPM decision making. *Curr. Opin. Insect. Sci.* 20, 84–89. https://doi.org/10.1016/j.cois.2017.03.009.

Giraldo, J. P., Wu, H., Newkirk, G. M. and Kruss, S. 2019. Nanobiotechnology approaches for engineering smart plant sensors. *Nat. Nanotechnol.* 14(6), 541–553. https://doi.org/10.1038/s41565-019-0470-6.

Glenn, D. M. and Tabb, A. 2019. Evaluation of five methods to measure normalized difference vegetation index (NDVI) in apple and citrus. *Int. J. Fruit. Sci.* 19(2), 191–210. https://doi.org/10.1080/15538362.2018.1502720.

Gogoi, N. K., Deka, B. and Bora, L. C. 2018. Remote sensing and its use in detection and monitoring plant diseases: A review. *Agric. Rev.* 39, 307–313.

Gouinguené, S. P. D., Poiger, T. and Städler, E. 2006. Eggs of cabbage root fly stimulate conspecific oviposition: Evaluation of the activity and determination of an egg-associated compound. *Chemoecology* 16(2), 107–113. https://doi.org/10.1007/s00049-006-0335-y.

Green, R. H. 1970. On fixed precision level sequential sampling. *Res. Popul. Ecol.* 12(2), 249–251. https://doi.org/10.1007/BF02511568.

Groher, T. 2019. *Suitability of non-destructive sensors for monitoring physiological and biochemical responses of tomato leaves and fruits to abiotic stresses*. PhD Dissertation. Rheinische Friedrich-Wilhelms-Universität, Bonn, DE.

Guarnieri, A., Maini, S., Molari, G. and Rondelli, V. 2011. Automatic trap for moth detection in integrated pest management. *Bull. Insectol.* 64, 247–251.

Guerin, P. M., Städler, E. and Buser, H. R. 1983. Identification of host plant attractants for the carrot fly, *Psila rosae*. *J. Chem. Ecol.* 9(7), 843–861. https://doi.org/10.1007/BF00987809.

Guerin, P. M. and Visser, J. H. 1980. Electroantennogram responses of the carrot fly, Psila rosae, to volatile plant components. *Physiol. Entomol.* 5(2), 111–119.

Guimapi, R. Y. A., Mohamed, S. A., Okeyo, G. O., Ndjomatchoua, F. T., Ekesi, S. and Tonnang, H. E. Z. 2016. Modeling the risk of invasion and spread of *Tuta absoluta* in Africa. *Ecol. Complexity* 28, 77–93.

Gupta, P. D. and Thorsteinson, A. J. 1960. Food plant relationships of the diamond-back moth (plutella maculipennis (Curt.)). I. Gustation and olfaction in relation to botanical specificity of the larvae. *Entomol. Exp. Appl.* 3(3), 241–250.

Gusmão, M. R., Picanço, M. C., Guedes, R. N. C., Galvan, T. L. and Pereira, E. J. G. 2006. Economic injury level and sequential sampling plan for Bemisia tabaci in outdoor tomato. *J. Appl. Entomol.* 130(3), 160–166. https://doi.org/10.1111/j.1439-0418.2005.01032.x.

Gusmão, M. R., Picanço, M. C., Zanuncio, J. C., Silva, D. J. H. and Barrigossi, J. A. F. 2005. Standardised sampling plan for Bemisia tabaci (Homoptera: Aleyrodidae) in outdoor tomatoes. *Sci. Hortic.* 103(4), 403–412. https://doi.org/10.1016/j.scienta.2004.04.005.

Halada, P., Hlavackova, K., Risueño, J., Berriatua, E., Volf, P. and Dvorak, V. 2018. Effect of trapping method on species identification of phlebotomine sandflies by MALDI-TOF MS protein profiling. *Med. Vet. Entomol.* 32(3), 388–392. https://doi.org/10.1111/mve.12305.

Hamby, K. A., E. Bellamy, D., Chiu, J. C., Lee, J. C., Walton, V. M., Wiman, N. G., York, R. M. and Biondi, A. 2016. Biotic and abiotic factors impacting development, behavior, phenology, and reproductive biology of Drosophila suzukii. *J. Pest Sci.* 89(3), 605–619. https://doi.org/10.1007/s10340-016-0756-5.

Hamilton, A. J., Endersby, N. M., Schellhorn, N. A., Ridland, P. M., Rogers, P. M., Jevremov, D. and Baker, G. 2006. Evaluation of fixed sample-size plans for *Plutella xylostella* (Lepidoptera: Plutellidae) on broccoli crops in Australia. *J. Econ. Entomol.* 99(6), 2171–2176.

Hamilton, A. J., Schellhorn, N. A., Endersby, N. M., Ridland, P. M. and Ward, S. A. 2004. A dynamic binomial sequential sampling plan for *Plutella xylostella* (Lepidoptera: Plutellidae) on Broccoli and cauliflower in Australia. *J. Econ. Entomol.* 97(1), 127–135. https://doi.org/10.1093/jee/97.1.127.

Hamilton, A. J., Waters, E. K., Kim, H. J., Pak, W. S. and Furlong, M. J. 2009a. Sampling a weighted pest complex: Caterpillars in North Korean cabbage (Brassica oleracea var. capitata) crops. *Entomol. Exp. Appl.* 130(3), 282–289. https://doi.org/10.1111/j.1570-7458.2008.00815.x.

Hamilton, A. J., Waters, E. K., Kim, H. J., Pak, W. S. and Furlong, M. J. 2009b. Validation of fixed sample size plans for monitoring lepidopteran pests of Brassica oleracea crops in North Korea. *J. Econ. Entomol.* 102(3), 1336–1343. https://doi.org/10.1603/029.102.0361.

Harmon, D. S., Haseeb, M., Kanga, L. H. B. and Liburd, O. E. 2019. Evaluation of monitoring traps and lures for Drosophila suzukii (Diptera: Drosophilidae) in Berry plantings in Florida. *Insects.* 10(10), 313.

Harvey, C. D. 2015. Integrated pest management in temperate horticulture: Seeing the wood for the trees. *CAB Rev.* 10(28), 1–13.

Henneberry, T. J., Forlow, J. L. and De La Torre, T. 2001. *Honeydew Production by Sweetpotato Whitefly Adults and Nymphs* (Cotton: A College of Agriculture Report). The University of Arizona College of Agriculture and Life Sciences, Arizona.

Higley, L. G. and Pedigo, L. P. 1996. *Economic Thresholds for Integrated Pest Management*. Lincoln, NE: University of Nebraska Press.

Higley, L. G. and Peterson, R. K. D. 2009. Economic decision rules for IPM. In: *Integrated Pest Management. Concepts, Tactics, Strategies and Case Studies*. Cambridge: Cambridge University Press, 25–32.

Hong, L. and Rumei, X. 1993. Studies on honeydew excretion by greenhouse whitefly, Trialeurodes vaporariorum (Westw.) on its host plant, Cucumis sativus. *J. Appl. Entomol.* 115(1–5), 43–51. https://doi.org/10.1111/j.1439-0418.1993.tb00362.x.

Hoshizaki, S., Koshikawa, N., Toyoda, T. and Ishikawa, Y. 2020. Oviposition in the onion fly Delia antiqua (Diptera: Anthomyiidae) is socially facilitated by visual cues. *Bull. Entomol. Res.* 110(6), 677–683. https://doi.org/10.1017/S0007485320000152.

Hoy, C. W. 1991. Variable-intensity sampling for proportion of plants infested with pests. *J. Econ. Entomol.* 84(1), 148–157. https://doi.org/10.1093/jee/84.1.148.

Hull, L. A. and Beers, E. H. 1990. Validation of injury thresholds for European red mite (Acari: Tetranychidae) on 'yorking' and 'delicious' apple. *J. Econ. Entomol.* 83(5), 2026–2031. https://doi.org/10.1093/jee/83.5.2026.

Hulspas-Jordaan, P. M. and van Lenteren, J. C. 1989. The parasite-host relationship between Encarsia formosa (Hymenoptera: Aphelinidae) and Trialeurodes vaporariorum (Homoptera: Aleyrodidae). *XXX. Modelling Population Growth of Greenhouse Whitefly on Tomato*. Agric. Univ. Wageningen Papers 89-2, 1–54. Available at: https://library.wur.nl/WebQuery/wurpubs/fulltext/468011.

Innocenzi, P. J., Hall, D. R. and Cross, J. V. 2001. Components of male aggregation pheromone of strawberry blossom weevil, Anthonomus rubi Herbst. (Coleoptera : Curculionidae). *J. Chem. Ecol.* 27(6), 1203–1218. https://doi.org/10.1023/A:1010320130073.

Ishikawa, Y., Ikeshoji, T. and Matsumoto, Y. 1978. A propylthio moiety essential to the oviposition attractant and stimulant of the onion fly, Hylemya antiqua MEIGEN. *Appl. Entomol. Zool.* 13(2), 115–122. https://doi.org/10.1303/aez.13.115.

Ishikawa, Y., Matsumoto, Y., Tsutsumi, M. and Mitsui, Y. 1984. Mixture of 2-phenylethanol and n-valeric acid, a new attractant for the onion and seed-corn flies, Hylemya antiqua and H. Platura : Diptera: Anthomyiidae. *Appl. Entomol. Zool.* 19(4), 448–455. https://doi.org/10.1303/aez.19.448.

Ishikawa, Y., Matsumoto, Y., Tsutsumi, M., Mitsui, Y., Yamashita, K., Yoshida, M. and Shirai, E. 1987. Controlled release formulation of attractant for the onion and seed-corn flies, Hylemya antiqua and H. platura: Diptera: Anthomyiidae. *Appl. Entomol. Zool.* 22(3), 303–309. https://doi.org/10.1303/aez.22.303.

Islam, M. N., Hasanuzzaman, A. T. M., Zhang, Z. F., Zhang, Y. and Liu, T. X. 2017. High level of nitrogen makes tomato plants releasing less volatiles and attracting more Bemisia tabaci (Hemiptera: Aleyrodidae). *Front. Plant Sci.* 8, 466. https://doi.org/10.3389/fpls.2017.00466.

Jaastad, G., Bengtsson, M., Anderson, P., Kobro, S., Knudsen, G. and Witzgall, P. 2002. Sex pheromone of apple fruit moth Argyresthia conjugella (Lepidoptera: Argyresthiidae). *Agric. For. Entomol.* 4(3), 233–236. https://doi.org/10.1046/j.1461-9563.2002.00140.x.

Jaleel, W., Saeed, S., Saeed, Q., Naqqash, M. N., Sial, M. U., Aine, Q. U., Yanyuan, L., Rui, Z., He, Y. and Lu, L. 2019. Effects of three different cultivars of cruciferous plants on the age-stage, two-sex life table traits of *Plutella xylostella* (L.) (Lepidoptera: Plutellidae). *Entomol. Res.* 49(4), 151–157. https://doi.org/10.1111/1748-5967.12270.

Jens, K. 1983. Bestemmelse af æg-og Puppe antal af gulerodsfluen (Psila rosae F.) ved indsamling af jordprøver. *Tidsskr. Planteavl.* 87, 379–387.

Jeon, H. Y., Kim, H. H., Yang, C. Y., Kang, T. J. and Kim, D.-S. 2009. A tentative economic injury level for greenhouse whitefly on cucumber plants in the protective cultivation. *Korean J. Hortic. Sci. Technol.* 27, 81–85.

Johansen, T. J. and Meadow, R. 2006. Population differences in emergence of Brassica Root Flies (Diptera: Anthomyiidae). *Environ. Entomol.* 35(5), 1161–1165. https://doi.org/10.1093/ee/35.5.1161.

Johnson, M. W., Caprio, L. C., Coughlin, J. A., Tabashnik, B. E., Rosenheim, J. A. and Welter, S. C. 1992. Effect of Trialeurodes vaporariorum (Homoptera: Aleyrodidae) on yield of fresh market tomatoes. *J. Econ. Entomol.* 85(6), 2370–2376.

Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A. and Landivar-Bowles, J. 2021. The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Curr. Opin. Biotechnol.* 70, 15–22. https://doi.org/10.1016/j.copbio.2020.09.003.

Kaiser, C., Walton, V., Tait, G. and Stacconi, M. V. R. 2021. *U.S. Patent Application No. 17/259,535*.

Kanmiya, K. 1996. Discovery of male acoustic signals in the greenhouse whitefly, Trialeurodes vaporariorum (Westwood) (Homoptera: Aleyrodidae). *Appl. Entomol. Zool.* 31(2), 255–262. https://doi.org/10.1303/aez.31.255.

Kanmiya, K. 2006. Mating behaviour and vibratory signals in whiteflies (Hemiptera: Aleyrodidae). In: *Physiology, Behaviour, Ecology, and Evolution (Contemporary Topics in Entomology)*. Boca Raton, FL: CRC Press, 365–379.

Kanmiya, K. and Sonobe, R. 2002. Records of two citrus pest whiteflies in Japan with special reference to their mating sounds (Homoptera: Aleyrodidae). *Appl. Entomol. Zool.* 37(3), 487–495. https://doi.org/10.1303/aez.2002.487.

Kergunteuil, A., Dugravot, S., Danner, H., van Dam, N. M. and Cortesero, A. M. 2015. Characterizing volatiles and attractiveness of five brassicaceous plants with potential for a ‘push-pull’ strategy Toward the cabbage root fly, Delia radicum. *J. Chem. Ecol.* 41(4), 330–339. https://doi.org/10.1007/s10886-015-0575-9.

Kergunteuil, A., Dugravot, S., Mortreuil, A., Ralec, A. L. and Cortesero, A. M. 2012. Selecting volatiles to protect brassicaceous crops against the cabbage root fly, Delia radicum. *Entomol. Exp. Appl.* 144(1), 69–77. https://doi.org/10.1111/j.1570-7458.2012.01257.x.

Kim, H. G., Park, J.-S. and Lee, D.-H. 2018. Potential of unmanned aerial sampling for monitoring insect populations in rice fields. *Fla. Entomol.* 101(2), 330–334. https://doi.org/10.1653/024.101.0229.

Kim, J.-K., Park, J.-J., Park, H. and Cho, K. 2001. Unbiased estimation of greenhouse whitefly, Trialeurodes vaporariorum, mean density using yellow sticky trap in cherry tomato greenhouses. *Entomol. Exp. Appl.* 100(2), 235–243. https://doi.org/10.1046/j.1570-7458.2001.00868.x.

Kinjo, H., Kunimi, Y., Ban, T. and Nakai, M. 2013. Oviposition efficacy of Drosophila suzukii (Diptera: Drosophilidae) on different cultivars of blueberry. *J. Econ. Entomol.* 106(4), 1767–1771. https://doi.org/10.1603/EC12505.

Kirkpatrick, D. M., McGhee, P. S., Gut, L. J. and Miller, J. R. 2017. Improving monitoring tools for spotted wing drosophila, Drosophila suzukii. *Entomol. Exp. Appl.* 164(2), 87–93. https://doi.org/10.1111/eea.12602.

Knight, A. 2010. Improved monitoring of female codling moth (Lepidoptera: Tortricidae) with pear ester plus acetic acid in sex pheromone-treated orchards. *Environ. Entomol.* 39(4), 1283–1290. https://doi.org/10.1603/EN10034.

Knight, A. L., Hilton, R., Basoalto, E. and Stelinski, L. L. 2014. Use of glacial acetic acid to enhance bisexual monitoring of tortricid pests with kairomone lures in pome fruits. *Environ. Entomol.* 43(6), 1628–1640. https://doi.org/10.1603/EN14153.

Knight, A. L., Hilton, R. and Light, D. M. 2005. Monitoring codling moth (Lepidoptera: Tortricidae) in apple with blends of ethyl (E, Z)-2,4-decadienoate and codlemone. *Environ. Entomol.* 34(3), 598–603. https://doi.org/10.1603/0046-225X-34.3.598.

Knight, A. L. and Light, D. M. 2005a. Developing action thresholds for codling moth (Lepidoptera: Tortricidae) with pear ester-and codlemone-baited traps in apple orchards treated with sex pheromone mating disruption. *Can. Entomol.* 137(6), 739–747.

Knight, A. L. and Light, D. M. 2005b. Timing of egg hatch by early-season codling moth (Lepidoptera: Tortricidae) predicted by moth catch in pear ester-and codlemone-baited traps. *Can. Entomol.* 137(6), 728–738.

Knight, A. L., Mujica, V. and Larsson Herrera, S. 2019. Addition of terpenoids to pear ester plus acetic acid increases catches of codling moth (Lepidoptera: Tortricidae). *J. Appl. Entomol.* 143, 812–821.

Knudsen, G. K., Norli, H. R. and Tasin, M. 2017. The ratio between field attractive and background volatiles encodes host-plant recognition in a specialist moth. *Front. Plant Sci.* 8, 2206. https://doi.org/10.3389/fpls.2017.02206.

Knudsen, G. K. and Tasin, M. 2015. Spotting the invaders: A monitoring system based on plant volatiles to forecast apple fruit moth attacks in apple orchards. *Basic Appl. Ecol.* 16(4), 354–364.

Kobro, S., Søreide, L., Djønne, E., Rafoss, T., Jaastad, G. and Witzgall, P. 2003. Masting of rowan Sorbus aucuparia L. and consequences for the apple fruit moth Argyresthia conjugella Zeller. *Popul. Ecol.* 45(1), 25–30. https://doi.org/10.1007/s10144-003-0136-x.

Koshihara, T., Yamada, H., Tamaki, Y. and Ando, T. 1978. Field attractiveness of the synthetic sex-pheromone of the diamondback Moth, *Plutella xylostella* (L.). *Appl. Entomol. Zool.* 13(2), 138–141. https://doi.org/10.1303/aez.13.138.

Kovanci, O. B., Kovanci, B. and Gencer, N. S. 2005. Sampling and development of economic injury levels for Anthonomus rubi Herbst adults. *Crop Prot.* 24(12), 1035–1041. https://doi.org/10.1016/j.cropro.2005.02.007.

Kumar, S. T. P., Mazumdar, D., Kamei, D. and Kamei, A. 2018. Advantages of artificial neural network over regression method in prediction of pest incidence in rice crop. *Int. J. Agric. Stat. Sci.* 14, 357–363.

Kumar, V. and Arora, K. 2020. Trends in nano-inspired biosensors for plants. *Mater. Sci. Energy Technol.* 3, 255–273. https://doi.org/10.1016/j.mset.2019.10.004.

Lamy, F., Dugravot, S., Cortesero, A. M., Chaminade, V., Faloya, V. and Poinsot, D. 2018. One more step toward a push-pull strategy combining both a trap crop and plant volatile organic compounds against the cabbage root fly Delia radicum. *Environ. Sci. Pollut. Res. Int.* 25(30), 29868–29879. https://doi.org/10.1007/s11356-017-9483-6.

Lamy, F. C., Poinsot, D., Cortesero, A. M. and Dugravot, S. 2017. Artificially applied plant volatile organic compounds modify the behavior of a pest with no adverse effect on its natural enemies in the field. *J. Pest Sci.* 90(2), 611–621.

Landolt, P. J., Suckling, D. M. and Judd, G. J. R. 2007. Positive interaction of a feeding attractant and a host kairomone for trapping the codling moth, *Cydia pomonella* (L.). *J. Chem. Ecol.* 33(12), 2236–2244. https://doi.org/10.1007/s10886-007-9391-1.

Leach, H., Van Timmeren, S., Wetzel, W. and Isaacs, R. 2019. Predicting Within- and between-year variation in activity of the invasive spotted wing drosophila (Diptera: Drosophilidae) in a temperate region. *Environ. Entomol.* 48(5), 1223–1233. https://doi.org/10.1093/ee/nvz101.

Lemmetty, A. and Vänninen, I. 2014. Bemisia tabaci biotype Q determined for the first time on poinsettia crops in Finland and Sweden. *Ann. Zool. Fenn.* 51(6), 501–506. http://doi.org/10.5735/086.051.0605.

Li, P., Zhu, J. and Qin, Y. 2012. Enhanced attraction of *Plutella xylostella* (Lepidoptera: Plutellidae) to pheromone-baited traps with the addition of green leaf volatiles. *J. Econ. Entomol.* 105(4), 1149–1156. https://doi.org/10.1603/EC11109.

Li, Z., Yu, T., Paul, R., Fan, J., Yang, Y. and Wei, Q. 2020. Agricultural nanodiagnostics for plant diseases: Recent advances and challenges. *Nanoscale Adv.* 2(8), 3083–3094. https://doi.org/10.1039/C9NA00724E.

Li, Z., Zalucki, M. P., Yonow, T., Kriticos, D. J., Bao, H., Chen, H., Hu, Z., Feng, X. and Furlong, M. J. 2016. Population dynamics and management of diamondback moth (*Plutella xylostella*) in China: The relative contributions of climate, natural enemies and cropping patterns. *Bull. Entomol. Res.* 106(2), 197–214.

Liao, Y.-C. and Yang, M.-M. 2015. Acoustic communication of three closely related psyllid species: A case study in clarifying allied species using substrate-borne signals (Hemiptera: Psyllidae: Cacopsylla). *Ann. Entomol. Soc. Am.* 108(5), 902–911. https://doi.org/10.1093/aesa/sav071.

Light, D. M., Knight, A. L., Henrick, C. A., Rajapaska, D., Lingren, B., Dickens, J. C., Reynolds, K. M., Buttery, R. G., Merrill, G., Roitman, J. and Campbell, B. C. 2001. A pear-derived kairomone with pheromonal potency that attracts male and female codling moth, *Cydia pomonella* (L.). *Naturwissenschaften.* 88(8), 333–338. https://doi.org/10.1007/s001140100243.

Löcken, H., Fischer, O. W., Selz, J. and Boppré, M. 2020. 'Drone-Netting' for sampling live insects. *J. Insect Sci.* 20(5), 3. https://doi.org/10.1093/jisesa/ieaa086.

Macfadyen, S., Davies, A. P. and Zalucki, M. P. 2015. Assessing the impact of arthropod natural enemies on crop pests at the field scale. *Insect Sci.* 22(1), 20–34. https://doi.org/10.1111/1744-7917.12174.

Magarey, R. D. and Isard, S. A. 2017. A troubleshooting guide for mechanistic plant pest forecast models. *J. Integr. Pest Manag.* 8. https://doi.org/10.1093/jipm/pmw015.

Maria, A. 1997. Introduction to modeling and simulation. In: Andradóttir, S., Healy, K. J., Withers, D. H. and Nelson, B. L. (Eds) *Proceedings of the 29th Winter Simulation Conference*, 7–13. New York: ACM Press.

Marques da Silva, J. R., Damásio, C. V., Sousa, A. M. O., Bugalho, L., Pessanha, L. and Quaresma, P. 2015. Agriculture pest and disease risk maps considering MSG satellite data and land surface temperature. *Int. J. Appl. Earth Obs. Geoinf.* 38, 40–50. https://doi.org/10.1016/j.jag.2014.12.016.

Marston, Z. P. D., Cira, T. M., Hodgson, E. W., Knight, J. F., Macrae, I. V. and Koch, R. L. 2020. Detection of stress induced by soybean aphid (Hemiptera: Aphididae) using multispectral imagery from unmanned aerial vehicles. *J. Econ. Entomol.* 113(2), 779–786. https://doi.org/10.1093/jee/toz306.

Matsumoto, B. Y. and Thorsteinson, A. J. 1968. Effect of organic sulfur compounds on oviposition in onion maggot, Hylemya antiqua MEIGEN (Diptera: Anthomyiidae). *Appl. Entomol. Zool.* 3(1), 5–12. https://doi.org/10.1303/aez.3.5.

McCarthy, A., Long, D. and Grundy, P. 2020. Smartphone apps under development to aid pest monitoring. *GRDC Update*. Available at: https://grdc.com.au/__data/assets/pdf_file/0028/430858/GRDC-Update-Paper-Long-Derek-July-2020.pdf.

McCravy, K. W. 2018. A review of sampling and monitoring methods for beneficial arthropods in agroecosystems. *Insects.* 9(4), 170. https://doi.org/10.3390/insects9040170.

McRoberts, N., Hall, C., Madden, L. V. and Hughes, G. 2011. Perceptions of disease risk: From social construction of subjective judgments to rational decision making. *Phytopathology.* 101(6), 654–665. https://doi.org/10.1094/PHYTO-04-10-0126.

Méndez-Vázquez, L. J., Lira-Noriega, A., Lasa-Covarrubias, R. and Cerdeira-Estrada, S. 2019. Delineation of site-specific management zones for pest control purposes: Exploring precision agriculture and species distribution modeling approaches. *Comput. Electron. Agric.* 167, 105101. https://doi.org/10.1016/j.compag.2019.105101.

Miller, J. R., Adams, C. G., Weston, P. A. and Schenker, J. H. 2015. *Trapping of Small Organisms Moving Randomly: Principles and Applications to Pest Monitoring and Management*. Cham/Heidelberg/New York/Dordrecht/London: Springer.

Milner-Gulland, E. J. and Shea, K. 2017. Embracing uncertainty in applied ecology. *J. Appl. Ecol.* 54(6), 2063–2068. https://doi.org/10.1111/1365-2664.12887.

Miluch, C. E., Dosdall, L. M. and Evenden, M. L. 2013. The potential for pheromone-based monitoring to predict larval populations of diamondback moth, *Plutella xylostella* (L.), in canola (*Brassica napus* L.). *Crop Prot.* 45, 89–97. https://doi.org/10.1016/j.cropro.2012.11.023.

Miluch, C. E., Dosdall, L. M. and Evenden, M. L. 2014. Factors influencing male *Plutella xylostella* (Lepidoptera: Plutellidae) capture rates in sex pheromone-baited traps on Canola in Western Canada. *J. Econ. Entomol.* 107(6), 2067–2076. https://doi.org/10.1603/EC13371.

Moerkens, R., Brenard, N., Bosmans, L., Reybroeck, E., Janssen, D., Hemming, J. and Sluydts, V. 2019. Protocol for semi-automatic identification of whiteflies *Bemisia tabaci* and *Trialeurodes vaporariorum* on yellow sticky traps. *J. Appl. Entomol.* 143(6), 652–658.

Moerkens, R., Janssen, D., Brenard, N., Reybroeck, E., del Mar Tellez, M., Rodríguez, E., Bosmans, L., Leirs, H. and Sluydts, V. 2020. Simplified modelling enhances biocontrol decision making in tomato greenhouses for three important pest species. *J. Pest. Sci.* 94(2), 285–295 https://doi.org/10.1007/s10340-020-01256-0.

Möhring, N., Wuepper, D., Musa, T. and Finger, R. 2020. Why farmers deviate from recommended pesticide timing: The role of uncertainty and information. *Pest. Manag. Sci.* 76(8), 2787–2798. https://doi.org/10.1002/ps.5826.

Mozūraitis, R., Hall, D., Trandem, N., Ralle, B., Tunström, K., Sigsgaard, L., Baroffio, C., Fountain, M., Cross, J., Wibe, A. and Borg-Karlson, A. K. 2020. Composition of strawberry floral volatiles and their effects on behavior of strawberry blossom weevil, Anthonomus rubi. *J. Chem. Ecol.* 46(11–12), 1069–1081. https://doi.org/10.1007/s10886-020-01221-2.

Muñiz, M. and Nombela, G. 2001. Differential variation in development of the B-and Q-biotypes of Bemisia tabaci (Homoptera: Aleyrodidae) on sweet pepper at constant temperatures. *Environ. Entomol.* 30(4), 720–727.

Murali-Baskaran, R. K., Sharma, K. C., Kaushal, P., Kumar, J., Parthiban, P., Senthil-Nathan, S. and Mankin, R. W. 2018. Role of kairomone in biological control of crop pests: A review. *Physiol. Mol. Plant* 101, 3–15.

Nakabayashi, H., Mizutani, K., Ebihara, T., Wakatsuki, N., Uga, H., Kubota, K. and Ishii, M. 2017. Biotype identification of Bemisia tabaci by acoustical method. *J. Agric. Inform.* 8(3), 11–22. https://doi.org/10.17700/jai.2017.8.3.391.

Naranjo, S. E. 2008. Sampling arthropods. In: Kluwer, P.-Z. (Ed.) *Encyclopedia of Entomology* (vol. 3). Dordrecht/Boston/London: Academic Press Publishers, 1933–1945.

Naranjo, S. E. and Hutchison, W. D. 1997. Validation of arthropod sampling plans using a resampling approach: Software and analysis. *Am. Entomol.* 43(1), 48–57.

Nava-Camberos, U., Riley, D. G. and Harris, M. K. 2001. Temperature and host plant effects on development, survival, and fecundity of Bemisia argentifolii (Homoptera: Aleyrodidae). *Environ. Entomol.* 30(1), 55–63. https://doi.org/10.1603/0046-225X-30.1.55.

Ngowi, B. V., Tonnang, H. E. Z., Mwangi, E. M., Johansson, T., Ambale, J., Ndegwa, P. N. and Subramanian, S. 2017. Temperature-dependent phenology of *Plutella xylostella* (Lepidoptera: Plutellidae): Simulation and visualization of current and future distributions along the Eastern Afromontane. *PLoS ONE* 12(3), e0173590. https://doi.org/10.1371/journal.pone.0173590.

Nguyen, H. D. and Nansen, C. 2020. Hyperspectral remote sensing to detect leafminer-induced stress in bok choy and spinach according to fertilizer regime and timing. *Pest Manag. Sci.* 76(6), 2208–2216.

Nissinen, A. 2008. *Towards ecological control of carrot Psyllid (Trioza apicalis)*. PhD Dissertation. University of Eastern Finland, Kuopio.

Nottingham, S. F. 1988. Host-plant finding for oviposition by adult cabbage root fly, Delia radicum. *J. Insect Physiol.* 34(3), 227–234.

Nottingham, S. F. and Coaker, T. H. 1985. The olfactory response of cabbage root fly Delia radicum to the host plant volatile allylisothiocyanate. *Entomol. Exp. Appl.* 39(3), 307–316. https://doi.org/10.1111/j.1570-7458.1985.tb00474.x.

Nottingham, S. F. and Coaker, T. H. 1987. Changes in flight track angles of cabbage root fly, Delia radicum, in diffuse clouds and discrete plumes of the host-plant volatile allylisothiocyanate. *Entomol. Exp. Appl.* 43(3), 275–278. https://doi.org/10.1111/j.1570-7458.1987.tb02222.x.

Nyrop, J. P. 1988. Sequential classification of prey/predator ratios with application to European red mite (Acari: Tetranychidae) and Typhlodromus pyri (Acari: Phytoseiidae) in New York apple orchards. *J. Econ. Entomol.* 81(1), 14–21. https://doi.org/10.1093/jee/81.1.14.

Nyrop, J. P., Agnello, A. M., Kovach, J. and Reissig, W. H. 1989. Binomial sequential classification sampling plans for European red mite (Acari: Tetranychidae) with special reference to performance criteria. *J. Econ. Entomol.* 82(2), 482–490. https://doi.org/10.1093/jee/82.2.482.

Nyrop, J. P., Binns, M. R., van der Werf, W. and Kovach, J. 1994. Cascading tripartite binomial classification plans to monitor European red mite (Acari,Tetranychidae) through a season; development and evaluation of a new methodology for pest monitoring. *Exp. Appl. Acarol.* 18(3), 123–153. https://doi.org/10.1007/BF02353682.

Olatinwo, R. and Hoogenboom, G. 2014. Chapter 4: Weather-based pest forecasting for efficient crop protection. In: Abrol, D. P. (Ed.) *Integrated Pest Management*. San Diego: Academic Press, 59–78. https://doi.org/10.1016/B978-0-12-398529-3.00005-1.

Opit, G. P., Margolies, D. C. and Nechols, J. R. 2003. Within-plant distribution of twospotted spider mite, Tetranychus urticae Koch (Acari: Tetranychidae), on ivy geranium: Development of a presence-absence sampling plan. *J. Econ. Entomol.* 96(2), 482–488. https://doi.org/10.1093/jee/96.2.482.

Orlandini, S., Magarey, R. D., Park, E. W., Sporleder, M. and Kroschel, J. 2017. Methods of Agroclimatology: Modeling approaches for pests and diseases. In: Hatfield, J. L., Sivakumar, M. V. K., Prueger, J. H. (Eds) *Agroclimatology: Linking Agriculture to Climate*. Agronomy Monographs 60. Madison, WI: ASA, CSSA, and SSSA, 453–488. https://doi.org/10.2134/agronmonogr60.2016.0027.

Ovcharenko, F. V. and Nikolaeva, Z. V. 2020. Особенности развития морковной МУХИ В условиях тверской области. [The features of carrot fly development under the conditions of Tver region]. *Вестник Алтайского Государственного Аграрного Университета*. 1, 31–37.

Panda, S. S., Hoogenboom, G. and Paz, J. O. 2010. Remote sensing and geospatial technological applications for site-specific management of fruit and nut crops: A review. *Remote Sens.* 2(8), 1973–1997. https://doi.org/10.3390/rs2081973.

Pannell, D. J. 1994. The value of information in herbicide decision making for weed control in Australian wheat crops. *J. Agric. Resour. Econ.* 19, 366–381.

Park, J., Park, K., Shin, K. and Cho, K. 2011a. Evaluation and comparison of effects of air and tomato leaf temperatures on the population dynamics of greenhouse whitefly (Trialeurodes vaporariorum) in cherry tomato grown in greenhouses. *Korean J. Hortic. Sci. Technol.* 29, 420–432.

Park, J.-J., Lee, J.-H., Shin, K.-I., Lee, S. E. and Cho, K. 2011b. Geostatistical analysis of the attractive distance of two different sizes of yellow sticky traps for greenhouse whitefly, Trialeurodes vaporariorum (Westwood) (Homoptera: Aleyrodidae), in cherry tomato greenhouses. *Aust. J. Entomol.* 50(2), 144–151. https://doi.org/10.1111/j.1440-6055.2010.00796.x.

Park, J.-J., Park, H., Kim, Y. H. and Cho, K. 2000. Application of sequential classification of prey/predator ratio test to Tetranychus urticae and Phytoseiulus persimilis system in greenhouse roses. *J. Asia-Pac. Entomol.* 3(2), 121–126. https://doi.org/10.1016/S1226-8615(08)60065-5.

Park, Y.-L., Cho, J. R., Choi, K.-H., Kim, H. R., Kim, J. W., Kim, S. J., Lee, D.-H., Park, C.-G. and Cho, Y. S. 2021. Advances, limitations, and future applications of aerospace and geospatial technologies for apple IPM. *Kor. Soc. Appl. Entomol.* 60, 135–143.

Pasquali, S., Soresina, C. and Gilioli, G. 2019. The effects of fecundity, mortality and distribution of the initial condition in phenological models. *Ecol. Modell.* 402, 45–58.

Pedigo, L. P. and Buntin, G. D. 1993. *Handbook of Sampling Methods for Arthropods in Agriculture*. Boca Raton, FL: CRC Press.

Pedigo, L. P., Hutchins, S. H. and Higley, L. G. 1986. Economic injury levels in theory and practice. *Annu. Rev. Entomol.* 31(1), 341–368.

Penuelas, J., Filella, I., Lloret, P., Munoz, F. and Vilajeliu, M. 1995. Reflectance assessment of mite effects on apple trees. *Int. J. Remote Sens.* 16(14), 2727–2733.

Pérez, D. E., Cantor, F., Rodríguez, D. and Cure, J. R. 2011. Dispersión de Encarsia formosa (Hymenoptera: Aphelinidae) parasitando *Trialeurodes vaporariorum* (Hemiptera: Aleyrodidae) en tomate bajo invernadero. *Rev. Colomb. Entomol.* 37, 210–216.

Peterson, R. K. D. and Hunt, T. E. 2003. The probabilistic economic injury level: Incorporating uncertainty into pest management decision-making. *J. Econ. Entomol.* 96(3), 536–542. https://doi.org/10.1603/0022-0493-96.3.536.

Phelps, K., Collier, R. H., Reader, R. J. and Finch, S. 1993. Monte Carlo simulation method for forecasting the timing of pest insect attacks. *Crop Prot.* 12(5), 335–342. https://doi.org/10.1016/0261-2194(93)90075-T.

Potamitis, I., Rigakis, I. and Fysarakis, K. 2015. Insect biometrics: Optoacoustic signal processing and its applications to remote monitoring of McPhail type traps. *PLoS ONE.* 10(11), e0140474. https://doi.org/10.1371/journal.pone.0140474.

Potamitis, I., Rigakis, I. and Tatlas, N. A. 2017. Automated surveillance of fruit flies. *Sensors (Basel).* 17(1), 110. https://doi.org/10.3390/s17010110.

Potamitis, I., Rigakis, I., Vidakis, N., Petousis, M. and Weber, M. 2018. Affordable bimodal optical sensors to spread the use of automated insect monitoring. *J. Sens.* 2018, 1–25.

Poudyal, D., Rosenqvist, E., Ottosen, C.-O., Poudyal, D., Rosenqvist, E. and Ottosen, C.-O. 2019. Phenotyping from lab to field – Tomato lines screened for heat stress using Fv/Fm maintain high fruit yield during thermal stress in the field. *Funct. Plant Biol.* 46, 44–55. https://doi.org/10.1071/FP17317.

Prabhakar, M. and Thirupathi, M. 2018. Remote sensing of pest and disease damage in different crops and cropping systems. In: *Agroforestry Opportunities for Enhancing Resilience to Climate Change in Rainfed Areas*. ICAR: Central Research Institute for Dryland Agriculture, Hyderabad, India, 170–179.

Prasad, Y. and Prabhakar, M. 2012. Pest monitoring and forecasting. In: Abrol, D. B. and Shankar, U. (Eds) *Integrated Pest Management: Principles and Practice*. Oxfordshire, UK: CABI Publishing, 41–57.

Pratheepa, M. and Antony, J. C. 2018. Outlook of various soft computing data preprocessing techniques to study the pest population dynamics in integrated pest management. In: *Soft Computing for Biological Systems*. Singapore: Springer, 187–200.

Preti, M., Verheggen, F. and Angeli, S. 2020. Insect pest monitoring with camera-equipped traps: Strengths and limitations. *J. Pest Sci.* 94(2), 203–217. https://doi.org/10.1007/s10340-020-01309-4.

Pusz-Bochenska, K., Perez-Lopez, E., Dumonceaux, T. J., Olivier, C. and Wist, T. J. 2020. A rapid, simple, laboratory and field-adaptable DNA extraction and diagnostic method suitable for insect-transmitted plant pathogen and insect identification. *Plant Health Prog.* 21(1), 63–68. https://doi.org/10.1094/PHP-09-19-0063-FI.

Radcliffe, E. B., Hutchison, W. D. and Cancelado, R. E. 2009. *Integrated Pest Management: Concepts, Tactics, Strategies and Case Studies*. Cambridge: Cambridge University Press.

Rao, P. N. and Lakshmikantha, B. P. 2020. Applications of geospatial technologies in plant health management. In: *Innovative Pest Management Approaches for the 21st Century*. Singapore: Springer Singapore Pte., 3–25.

Reddy, G. V. P. and Guerrero, A. 2000. Pheromone-based integrated pest management to control the diamondback moth *Plutella xylostella* in cabbage fields. *Pest Manag. Sci.* 56(10), 882–888. https://doi.org/10.1002/1526-4998(200010)56:10<882::AID-PS226>3.0.CO;2-T.

Renwick, J. A. A., Haribal, M., Gouinguené, S. and Städler, E. 2006. Isothiocyanates stimulating oviposition by the diamondback moth, *Plutella xylostella*. *J. Chem. Ecol.* 32(4), 755–766. https://doi.org/10.1007/s10886-006-9036-9.

Rigakis, I., Potamitis, I., Tatlas, N.-A., Livadaras, I. and Ntalampiras, S. 2019. A multispectral backscattered light recorder of insects' wingbeats. *Electronics.* 8(3), 277. https://doi.org/10.3390/electronics8030277.

Rincon, D. F., Hoy, C. W. and Cañas, L. A. 2015. Generating within-plant spatial distributions of an insect herbivore based on aggregation patterns and per-node infestation probabilities. *Environ. Entomol.* 44(2), 194–209. https://doi.org/10.1093/ee/nvu022.

Rincon, D. F., Rivera-Trujillo, H. F., Mojica-Ramos, L. and Borrero-Echeverry, F. 2020. *Revisiting Pest Sampling Plans in Light of Economic Uncertainty and Risk Aversion*. AgriXiv preprint. 22 p. https://doi.org/10.31220/osf.io/swxpe.

Rodríguez, H. A. B. 2016. *A spatially explicit individual-based model of the population dynamics of the greenhouse whitefly (Trialeurodes vaporariorum), Encarsia formosa and tomato powdery mildew (Oidium neolycopersici) in tomato crops*. PhD Dissertation. Georg-August-University Göttingen, Göttingen, Germany.

Rodriguez-Saona, C., Firbas, N., Hernández-Cumplido, J., Holdcraft, R., Michel, C., Palacios-Castro, S. and Silva, D. B. 2020. Interpreting temporal and spatial variation in spotted-wing drosophila (Diptera: Drosophilidae) trap captures in highbush blueberries. *J. Econ. Entomol.* 113(5), 2362–2371. https://doi.org/10.1093/jee/toaa153.

Roosjen, P. P., Kellenberger, B., Kooistra, L., Green, D. R. and Fahrentrapp, J. 2020. Deep learning for automated detection of Drosophila suzukii: Potential for UAV-based monitoring. *Pest. Manag. Sci.* 76(9), 2994–3002. https://doi.org/10.1002/ps.5845.

Rossi Stacconi, M., Tait, G., Nieri, R., Chave, R., Park, K., Blood, R. and Walton, V. M. 2020a. A new food-grade behavior disruptor as a management tool for spotted-wing drosophila. *Presented at the Website of North American Raspberry and Blackberry Growers*, 1.

Rossi Stacconi, M. V., Tait, G., Rendon, D., Grassi, A., Boyer, G., Nieri, R. and Walton, V. M. 2020b. Gumming up the works: Field tests of a new food-grade gum as behavioral disruptor for Drosophila suzukii (Diptera: Drosophilidae). *J. Econ. Entomol.* 113(4), 1872–1880. https://doi.org/10.1093/jee/toaa072.

Roşu-Mareş, S., Şofron, A. and Moldovan, C. 2020. Preliminary results on the changes in the flight dynamic of *Cydia pomonella* (L.) in North-Eastern Transylvania, under the influence of climate change. *Sci. Pap. Ser. B Hortic.* 64, 183–185.

Rumei, X. and Liying, Z. 1991. Functional relationship between pest abundance, plant physiology and yield as exemplified by the greenhouse whitefly, Trialeurodes vaporariorum Westw. (Hom., Aleyrodidae). *J. Appl. Entomol.* 112(1–5), 370–381. https://doi.org/10.1111/j.1439-0418.1991.tb01070.x.

Samietz, J., Stoeckli, S., Hirschi, M., Spirig, C., Höhn, H., Calanca, P. and Rotach, M. 2013. Impact of climate change on phenology and sustainable management of the codling moth (Cydia pomonella). *Impact Clim. Chang. Phenol. Sustain. Manag. Codling Moth Cydia Pomonella*. 91, 449–457.

Saussure, S. 2019. *Interactions Between the Cereal Aphid Pests Sitobion avenae and Rhopalosiphum Padi and Their Fungal Natural Enemies*. Ås: Norwegian University of Life Sciences.

Savage, J., Fortier, A.-M., Fournier, F. and Bellavance, V. 2016. Identification of Delia pest species (Diptera: Anthomyiidae) in cultivated crucifers and other vegetable crops in Canada. *Can. J. Arthropod. Identif.* 29, 1–40. https://doi.org/10.3752/cjai.2016.29.

Schmera, D. and Guerin, P. M. 2012. Plant volatile compounds shorten reaction time and enhance attraction of the codling moth (Cydia pomonella) to codlemone. *Pest. Manag. Sci.* 68(3), 454–461. https://doi.org/10.1002/ps.2292.

Shaked, B., Amore, A., Ioannou, C., Valdés, F., Alorda, B., Papanastasiou, S., Goldshtein, E., Shenderey, C., Leza, M., Pontikakos, C., Perdikis, D., Tsiligiridis, T., Tabilio, M. R., Sciarretta, A., Barceló, C., Athanassiou, C., Miranda, M. A., Alchanatis, V., Papadopoulos, N. and Nestel, D. 2018. Electronic traps for detection and population monitoring of adult fruit flies (Diptera: Tephritidae). *J. Appl. Entomol.* 142(1–2), 43–51. https://doi.org/10.1111/jen.12422.

Shannag, H. G. and Freihat, N. M. 2009. Gas exchange of cucumber, Cucumis sativus L., impaired by tobacco whitefly, Bemisia tabaci (Gennadius)(Hemiptera: Aleyrodidae). *Jordan J. Agric. Sci.* 5, 295–305.

Shearer, P. W., West, J. D., Walton, V. M., Brown, P. H., Svetec, N. and Chiu, J. C. 2016. Seasonal cues induce phenotypic plasticity of Drosophila suzukii to enhance winter survival. *BMC Ecol.* 16, 11. https://doi.org/10.1186/s12898-016-0070-3.

Smith, E. A., Fuchs, M., Shields, E. J. and Nault, B. A. 2015. Long-distance dispersal potential for onion thrips (Thysanoptera: Thripidae) and iris yellow spot virus (Bunyaviridae: Tospovirus) in an onion ecosystem. *Environ. Entomol.* 44(4), 921–930. https://doi.org/10.1093/ee/nvv072.

Stockton, D. G., Wallingford, A. K. and Loeb, G. M. 2018. Phenotypic plasticity promotes overwintering survival in a globally invasive crop pest, Drosophila suzukii. *Insects.* 9(3), 105. https://doi.org/10.3390/insects9030105.

Stukenberg, N., Gebauer, K. and Poehling, H.-M. 2015. Light emitting diode (LED)-based trapping of the greenhouse whitefly (*Trialeurodes vaporariorum*). *J. Appl. Entomol.* 139(4), 268–279. https://doi.org/10.1111/jen.12172.

Stukenberg, N. M. 2018. *LED based trapping of whiteflies and fungus gnats: From visual ecology to application*. Doctoral Thesis. Leibniz Universität, Hannover. http://doi.org/10.15488/4144.

Su, Q., Chen, G., Mescher, M. C., Peng, Z., Xie, W., Wang, S., Wu, Q., Liu, J., Li, C., Wang, W. and Zhang, Y. 2018. Whitefly aggregation on tomato is mediated by feeding-induced changes in plant metabolites that influence the behaviour and performance of conspecifics. *Funct. Ecol.* 32(5), 1180–1193. https://doi.org/10.1111/1365-2435.13055.

Suckling, D. M., Stanbury, M. E., Lennon, O., Colhoun, K. M., Chinellato, F. and El-Sayed, A. M. 2020. Kairomone and camera trapping New Zealand flower thrips, *Thrips obscuratus*. *Insects* 11(9), 622.

Sumner-Kalkun, J. C., Sjölund, M. J., Arnsdorf, Y. M., Carnegie, M., Highet, F., Ouvrard, D., Greenslade, A. F. C., Bell, J. R., Sigvald, R. and Kenyon, D. M. 2020. A diagnostic real-time PCR assay for the rapid identification of the tomato-potato psyllid, Bactericera cockerelli (Šulc, 1909) and development of a psyllid barcoding database. *PLoS One*. 15(3), e0230741. https://doi.org/10.1371/journal.pone.0230741.

Tait, G., Park, K., Nieri, R., Crava, M. C., Mermer, S., Clappa, E., Boyer, G., Dalton, D. T., Carlin, S., Brewer, L., Walton, V. M., Anfora, G. and Rossi-Stacconi, M. V. 2020. Reproductive site selection: Evidence of an oviposition cue in a highly adaptive Dipteran, Drosophila suzukii (Diptera: Drosophilidae). *Environ. Entomol.* 49(2), 355–363. https://doi.org/10.1093/ee/nvaa005.

Tay, A., Lafont, F. and Balmat, J.-F. 2020. Forecasting pest risk level in roses greenhouse: Adaptive neuro-fuzzy inference system vs artificial neural networks. *Inf. Process. Agric.* 8(3), 386–397. https://doi.org/10.1016/j.inpa.2020.10.005.

te Beest, D. E., Paveley, N. D., Shaw, M. W. and van den Bosch, F. 2013. Accounting for the economic risk caused by variation in disease severity in fungicide dose decisions, exemplified for Mycosphaerella graminicola on winter wheat. *Phytopathology*. 103(7), 666–672. https://doi.org/10.1094/PHYTO-05-12-0119-R.

Teickner, H., Lehmann, J. R. K., Guth, P., Meinking, F. and Ott, D. 2019. Recognize the little ones: UAS-based in-situ fluorescent tracer detection. *Drones*. 3(1), 20. https://doi.org/10.3390/drones3010020.

Thistlewood, H. M. A., Gill, P., Beers, E. H., Shearer, P. W., Walsh, D. B., Rozema, B. M., Acheampong, S., Castagnoli, S., Yee, W. L., Smytheman, P. and Whitener, A. B. 2018. Spatial analysis of seasonal dynamics and overwintering of *Drosophila suzukii* (Diptera: Drosophilidae) in the Okanagan-Columbia Basin, 2010–2014. *Environ. Entomol.* 47(2), 221–232.

Thöming, G., Schjoll, A. F. and Johansen, T. J. 2017. Developing tools for monitoring and forecasting of onion fly Delia antiqua in Norway. In: *Proceedings of the Working Group "Integrated Protection in Field Vegetables"*, Arenenberg, Switzerland, 2–6. IOBC WPRS Bull.

Tochen, S., Woltz, J. M., Dalton, D. T., Lee, J. C., Wiman, N. G. and Walton, V. M. 2016. Humidity affects populations of *Drosophila suzukii* (Diptera: Drosophilidae) in blueberry. *J. Appl. Entomol.* 140(1–2), 47–57. https://doi.org/10.1111/jen.12247.

Tonina, L., Grassi, A., Caruso, S., Mori, N., Gottardello, A., Anfora, G., Giomi, F., Vaccari, G. and Ioriatti, C. 2018. Comparison of attractants for monitoring *Drosophila suzukii* in sweet cherry orchards in Italy. *J. Appl. Entomol.* 142(1–2), 18–25. https://doi.org/10.1111/jen.12416.

Tonnang, H. E. Z., Hervé, B. D. B., Biber-Freudenberger, L., Salifu, D., Subramanian, S., Ngowi, V. B., Guimapi, R. Y. A., Anani, B., Kakmeni, F. M. M., Affognon, H., Niassy, S., Landmann, T., Ndjomatchoua, F. T., Pedro, S. A., Johansson, T., Tanga, C. M., Nana, P., Fiaboe, K. M., Mohamed, S. F., Maniania, N. K., Nedorezov, L. V., Ekesi, S. and Borgemeister, C. 2017. Advances in crop insect modelling methods—Towards a whole system approach. *Ecol. Modell.* 354, 88–103. https://doi.org/10.1016/j.ecolmodel.2017.03.015.

Tonnang, H. E. Z., Nedorezov, L. V., Ochanda, H., Owino, J. and Löhr, B. 2009. Assessing the impact of biological control of *Plutella xylostella* through the application of Lotka–Volterra model. *Ecol. Modell.* 220(1), 60–70. https://doi.org/10.1016/j.ecolmodel.2008.09.002.

Tonnang, H. E. Z., Nedorezov, L. V., Owino, J. O., Ochanda, H. and Löhr, B. 2010. Host-parasitoid population density prediction using artificial neural networks: Diamondback moth and its natural enemies. *Agric. For. Entomol.* 12, 233–242. https://doi.org/10.1111/j.1461-9563.2009.00466.x.

Tran, A. K. and Koch, R. L. 2017. Spatial patterns and sequential sampling plans for predators of Aphis glycines (Hemiptera: Aphididae) in Minnesota Soybean. *Environ. Entomol.* 46(3), 663–673. https://doi.org/10.1093/ee/nvx040.

Tuovinen, T. 1987. *Pihlajanmarjakoin ennustemenetelmä (Tiedote No. 12/1987), MTT Tiedote*. Jokioinen: Maatalouden tutkimuskeskus.

van der Werf, W., Nyrop, J. P., Binns, M. R. and Kovach, J. 1997. Adaptive frequency classification: A new methodology for pest monitoring and its application to European red mite (Panonychus ulmi, Acari: Tetranychidae). *Exp. Appl. Acarol.* 21(6/7), 431–462. https://doi.org/10.1023/A:1018431912984.

Van Der Werf, W., Nyrop, J. P. and Hardman, J. M. 1994. Sampling predator/prey ratios to predict cumulative pest density in the mite-predatory mite system *Panonychus ulmi–Typhlodromus pyri* in apples. Asp. *Appl. Biol.* 37, 41–51.

Vanegas, F., Bratanov, D., Powell, K., Weiss, J. and Gonzalez, F. 2018. A novel methodology for improving plant pest surveillance in vineyards and crops using UAV-based hyperspectral and spatial data. *Sensors (Basel).* 18(1), 260. https://doi.org/10.3390/s18010260.

van Roermund, H. J. W. and van Lenteren, J. C. 1992. *The Parasite-Host Relationship Between Encarsia formosa (Hymenoptera: Aphelinidae) and Trialeurodes vaporariorum (Homoptera: Aleyrodidae) XXXV. Life-History Parameters of the Greenhouse Whitefly Parasitoid Encarsia formosa as a Function of Host Stage and Temperature*. Wageningen Agr. Univ. Papers 92-3, 1–147. Available at: https://library.wur.nl/WebQuery/wurpubs/fulltext/281747.

van Roermund, H. J. W., van Lenteren, J. C. and Rabbinge, R. 1997. Biological control of greenhouse whitefly with the parasitoid *Encarsia formosaon* tomato: An individual-based simulation approach. *Biol. Control.* 9(1), 25–47. https://doi.org/10.1006/bcon.1997.0512.

Vänninen, I., Pereira-Querol, M. and Engeström, Y. 2015. Generating transformative agency among horticultural producers: An activity-theoretical approach to transforming integrated pest management. *Agric. Syst.* 139, 38–49.

Vesali, F., Omid, M., Mobli, H. and Kaleita, A. 2017. Feasibility of using smart phones to estimate chlorophyll content in corn plants. *Photosynthetica* 55(4), 603–610. https://doi.org/10.1007/s11099-016-0677-9.

Villeneuve, F. and Latour, F. 2017. A few biological specificities of the carrot root fly (Psila rosae Fabre) for a more accurate forecasting in carrot (Daucus carota L.) production. *Acta Hortic.* 1153, 193–200. https://doi.org/10.17660/ActaHortic.2017.1153.28.

Walters, J. P., Archer, D. W., Sassenrath, G. F., Hendrickson, J. R., Hanson, J. D., Halloran, J. M., Vadas, P. and Alarcon, V. J. 2016. Exploring agricultural production systems and their fundamental components with system dynamics modelling. *Ecol. Modell.* 333, 51–65. https://doi.org/10.1016/j.ecolmodel.2016.04.015.

Wang, K. and Tsai, J. H. 1996. Temperature effect on development and reproduction of silverleaf whitefly (Homoptera: Aleyrodidae). *Ann. Entomol. Soc. Am.* 89(3), 375–384. https://doi.org/10.1093/aesa/89.3.375.

Wang, Y.-H., Hu, X.-M., Lin, X.-H., Geng, W.-H. and An, D.-R. 2011. Pest control efficacy of yellow board and sex pheromone on Trialeurodes vaporariorum. 西北農業學報 *Northwest Agric. J.* 20, 194–198.

Weersink, A., Fraser, E., Pannell, D., Duncan, E. and Rotz, S. 2018. Opportunities and challenges for big data in agricultural and environmental analysis. *Annu. Rev. Resour. Econ.* 10(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654.

Wen, C., Wu, D., Hu, H. and Pan, W. 2015. Pose estimation-dependent identification method for field moth images using deep learning architecture. *Biosyst. Eng.* 136, 117–128. https://doi.org/10.1016/j.biosystemseng.2015.06.002.

Whitfield, G. H., Carruthers, R. I., Lampert, E. P. and Haynes, D. L. 1985. Spatial and temporal distribution of plant damage caused by the onion maggot (Diptera: Anthomyiidae). *Environ. Entomol.* 14(3), 262–266. https://doi.org/10.1093/ee/14.3.262.

Willett, D. S., Filgueiras, C. C., Nyrop, J. P. and Nault, B. A. 2020. Field monitoring of onion maggot (Delia antiqua) fly through improved trapping. *J. Appl. Entomol.* 144(5), 382–387. https://doi.org/10.1111/jen.12740.

Williams, D. 2016. *Development of mass-trapping methods for Codling Moth females in disrupted orchards* (Final Report, Project Number: MT12000). Horticulture Innovation Australia Limited, Sydney.

Wiman, N. G., Walton, V. M., Dalton, D. T., Anfora, G., Burrack, H. J., Chiu, J. C., Daane, K. M., Grassi, A., Miller, B., Tochen, S., Wang, X. and Ioriatti, C. 2014. Integrating temperature-dependent life table data into a matrix projection model for Drosophila suzukii population estimation. *PLoS One.* 9(9), e106909. https://doi.org/10.1371/journal.pone.0106909.

Witzgall, P., Kirsch, P. and Cork, A. 2010. Sex pheromones and their impact on pest management. *J. Chem. Ecol.* 36(1), 80–100. https://doi.org/10.1007/s10886-009-9737-y.

Wong, J. S., Wallingford, A. K., Loeb, G. M. and Lee, J. C. 2018. Physiological status of Drosophila suzukii (Diptera: Drosophilidae) affects their response to attractive odours. *J. Appl. Entomol.* 142(5), 473–482. https://doi.org/10.1111/jen.12497.

Yan, Y., Feng, C. C., Wan, M. P. H. and Chang, K. T. T. 2015. Multiple regression and artificial neural network for the prediction of crop pest risks. In: International Conference on Information Systems for Crisis Response and Management in Mediterranean Countries. Second International Conference ISCRAM-med 2015, Tunis, Tunisia, October 28–30, 2015. Proceedings. Cham: Springer, 73–84.

Yanagisawa, R., Suwa, R., Takanashi, T. and Tatsuta, H. 2020. Substrate-borne vibrations reduced the density of tobacco whitefly Bemisia tabaci (Hemiptera: Aleyrodidae) infestations on tomato, Solanum Lycopersicum: An experimental assessment. *Appl. Entomol. Zool.* 56(2), 157–163. https://doi.org/10.1007/s13355-020-00711-9.

Yang, C. and Everitt, J. H. 2011. Remote sensing for detecting and mapping whitefly (*Bemisia tabaci*) infestations. In: Thompson, W. M. O. (Ed.) *The Whitefly, Bemisia tabaci (Homoptera: Aleyrodidae) Interaction with Geminivirus-Infected Host Plants: Bemisia tabaci, Host Plants and Geminiviruses*. Dordrecht: Springer Netherlands, 357–381. https://doi.org/10.1007/978-94-007-1524-0_13.

Yang, L., Peng, L., Zhang, L.-M., Zhang, L.-L. and Yang, S. 2009. A prediction model for population occurrence of paddy stem borer (*Scirpophaga incertulas*), based on back propagation artificial neural network and principal components analysis. *Comput. Electron. Agric.* 68(2), 200–206. https://doi.org/10.1016/j.compag.2009.06.003.

Yano, E., van Lenteren, J. C., Rabbinge, R. van Vianen, A. and Dorsman, R. 1989. The parasite-host relationship between *Encarsia formosa* (Hymenoptera: Aphelinidae) and *Trialeurodes vaporariorum* (Homoptera: Aleyrodidae). *XXXII. Simulation Studies of the Population Growth of Greenhouse Whitefly on Egg Plant, Cucumber, Sweet Pepper and Gerbera*. Wageningen Agric. Univ. Papers 89-2, 75–99. Available at: https://library.wur.nl/WebQuery/wurpubs/fulltext/218439.

Yeow, K. and Becker, M. 2018. JIS: Pest population prognosis with escalator boxcar train. *Presented at the 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Bangkok, TH, 381–385. https://doi.org/10.1109/IEEM.2018.8607724.

Yin, L. T. and Maschwitz, U. 1983. Sexual pheromone in the Green House Whitefly Trialeurodes vaporariorum Westw. *Z. Angew. Entomol.* 95(1–5), 439–446. https://doi.org/10.1111/j.1439-0418.1983.tb02665.x.

Zahner, P. and Baumgaertner, J. 1984. Sampling statistics for Panonychus ulmi (Koch) (Acarina, Tetranychidae) and Tetranychus urticae Koch (Acarina, Tetranychidae) feeding on apple trees. *Res. Popul. Ecol.* 26(1), 97–112. https://doi.org/10.1007/BF02515510.

Zalucki, M. P. and Furlong, M. J. 2008. Predicting outbreaks of a migratory pest: An analysis of DBM distribution and abundance. In: *The Management of the Diamondback Moth and Other Crucifer Insect Pests*. *Presented at the Fifth International Workshop*. Beijing, China: China Agricultural Science and Technology Press, 122–131.

Zalucki, M. P., Li, Z. Y., Yonow, T., Kriticos, D., Furlong, M. J. and Feng, X. 2017. Modelling the population dynamics & management of diamondback moth: The role of climate, natural enemies & cropping patterns. *Mysore J. Agric. Sci.* 51, 9–17.

Zaza, C., Bimonte, S., Faccilongo, N., La Sala, P., Contò, F. and Gallo, C. 2018. A new decision-support system for the historical analysis of integrated pest management activities on olive crops based on climatic data. *Comput. Electron. Agric.* 148, 237–249. https://doi.org/10.1016/j.compag.2018.03.015.

Zerulla, F. N., Capezzone, F. and Zebitz, C. P. W. 2016. Field performance of different lures for Drosophila suzukii. *Presented at the 17th International Conference on Organic Fruit-Growing*, Hohenheim, DE.

Zhang, J., Huang, Y., Pu, R., Gonzalez-Moreno, P., Yuan, L., Wu, K. and Huang, W. 2019. Monitoring plant diseases and pests through remote sensing technology: A review. *Comput. Electron. Agric.* 165, 104943. https://doi.org/10.1016/j.compag.2019.104943.

Zhang, W. and Swinton, S. M. 2009. Incorporating natural enemies in an economic threshold for dynamically optimal pest management. *Ecol. Modell.* 220(9–10), 1315–1324. https://doi.org/10.1016/j.ecolmodel.2009.01.027.

Zhang, W. and Swinton, S. M. 2012. Optimal control of soybean aphid in the presence of natural enemies and the implied value of their ecosystem services. *J. Environ. Manage.* 96(1), 7–16. https://doi.org/10.1016/j.jenvman.2011.10.008.

Zhu, L., Li, Z., Zhang, S., Xu, B., Zhang, Y., Zalucki, M. P., Wu, Q. and Yin, X. 2018. Population dynamics of the diamondback moth, *Plutella xylostella* (L.), in northern China: The effects of migration, cropping patterns and climate. *Pest. Manag. Sci.* 74(8), 1845–1853. https://doi.org/10.1002/ps.4885.