Pest monitoring and forecasting

Chapter · December 2012

2 authors:

Prabhakar Mathyam
Central Research Institute for Dryland Agriculture, India

Prasad Yen
Central Research Institute for Dryland Agriculture

3 Pest Monitoring and Forecasting

Yenumula G. Prasad and Mathyam Prabhakar
Division of Crop Sciences, Central Research Institute for Dryland Agriculure, Hyderabad, India

3.1 Introduction

Monitoring for pests is a fundamental first step in creating a proper integrated pest management (IPM) programme. Pests are monitored through a variety of monitoring tools such as pheromone traps, light traps, coloured sticky traps, pitfall traps and suction traps. The trap capture data serves several purposes: (i) ecological studies (Pathak, 1968; Crummay and Atkinson, 1997; Hirao *et al.*, 2008); (ii) tracking insect migration (Drake *et al.*, 2002); (iii) timing of pest arrivals into agroecosystems (Klueken *et al.*, 2009); (iv) initiating field scouting and sampling procedures; (v) timing of pesticide applications (Lewis, 1981; Merril *et al.*, 2010); (vi) starting date or biofix for phenology models (Knutson and Muegge, 2010); and (vii) prediction of later generations based on size of earlier generations (Zalucki and Furlong, 2005). Forecast for pests is an important component of the IPM strategy. Early warnings and forecasts based on biophysical methods provide lead time for managing impending pest attacks and can thus minimize crop loss, optimize pest control and reduce the cost of cultivation. Prevailing and anticipated weather information can help in crop planning and scheduling spray and farm operations to maximize crop yields and returns. Computer models have been developed to support various aspects of crop management in general and plant protection in particular and are widely in use in developed countries. A decision support system integrates a user-friendly front end to often complex models, knowledge bases, expert systems and database technologies. Decision support systems have emerged as essential tools to bridge the gap between science-based technology and end-users who make day-to-day management decisions. Web-based models and decision support systems are becoming popular and in future may become an abosolute requirement for local, regional/area-wide and international implementation of IPM systems (Waheed *et al.*, 2003). This chapter undertakes a selective review of published work on insect pest monitoring and forecasting and therefore is neither comprehensive nor exhaustive in its coverage.

3.2 Pest Monitoring through Traps

Among the various methods and devices used in pest monitoring, the most popular and widely used are sex pheromone traps for selective monitoring of individual flying species and light traps for flying species that are attracted to light. While adult males

(eds D.P. Abrol and U. Shankar)

are mostly caught in sex pheromone traps, adults of both sexes are trapped in light traps.

3.2.1 Sex pheromone traps

Pheromones are chemicals for species-specific communication. Most often, these sex pheromones are produced by females to attract a mate and are most well known for adult Lepidoptera. Commercially produced by synthesizing and blending the appropriate chemicals, the sex pheromones are loaded into dispensers, which can be placed in traps of various designs for deployment in agriculture, horticulture, forestry and storage. Pheromone traps are the most popular and widely used tools for pest detection and population monitoring. Pheromone traps have been exploited for three useful applications: (i) monitoring; (ii) mass trapping; and (iii) mating disruption. The most important and widespread practical applications of sex pheromones in pest management have been reviewed recently (Witzgall *et al.*, 2010). Population monitoring relates trap captures to the abundance of, or to the damage caused by, an insect species. The numbers caught over time have been used for initiating field scouting for egg laying, and assessing the need for timing of control measures based on action thresholds (Wall *et al.*, 1987; Gurrero and Reddy, 2001). However, traps do not always accurately indicate the overall pest pressure for use as thresholds for action, as trap catches are influenced by the efficacy of the lure, the dispenser (Arn *et al.*, 1997), the trap design (Fadamiro, 2004; Spear-O'Mara and Allen, 2007) and the trap location (Reardon *et al.*, 2006; Gallardo *et al.*, 2009). Pheromone traps are the most effective and sensitive enough to detect low-density populations. They are therefore handy tools for tracking invasive species in the establishment phase (El-Sayed *et al.*, 2006; Liebhold and Tobin, 2008) or for population monitoring to determine the extent of an outbreak area and the effectiveness of eradication campaigns (Cannon *et al.*, 2004).

The timing of adult male catches in the trap indicates the start of the pest flight activity in the area. This information is important for some pests, as it is used as the biofix date for accumulation of heat units above a base temperature in phenology models or sustained first flight for others (Knutson and Muegge, 2010).

Sex pheromone traps are useful for monitoring difficult pests that evade early detection of economic damage when a trap catch is used to calculate: (i) growing degree-days (GDD) for onset and completion of moth emergence (Spear-O'Mara and Allen, 2007; Knutson and Muegge, 2010); (ii) starting dates of egg hatch (Isaacs and van Timmeren, 2009); and (iii) onset of first larval damage (Knutson and Muegge, 2010). A linear relationship between male catches in sex pheromone traps and GDD is possible after appropriate transformation of variables (Gallardo *et al.*, 2009), and in some cases variability is better explained by including other variables related to density of host plants or suitable plant parts (Spear-O'Mara and Allen, 2007). Validation of the degree-day model is done by comparing the timing of predicted and observed phenological events through field scouting and damage assessments, and estimating the prediction accuracy and error (Knutson and Muegge, 2010).

Monitoring through a network of sites is most useful for studying spatial distributions of pests, early detection of infestations and identification of hot-spot locations to initiate appropriate management interventions on a spatial scale. Monitoring at the regional level improves the reliability of population monitoring for implementation of appropriate area-wide IPM systems (Ayalew *et al.*, 2008). Moth captures in a network of pheromone trap sites established across the Canadian prairies, when used in conjunction with backward trajectories provided by meteorological services, were helpful in providing early detection of diamondback moth infestations (Hopkinson and Soroka, 2010). Peak trap captures are often correlated with associated weather to identify positive or negative influences of weather parameters on moth activity and pest build-up (Gwadi *et al.*, 2006; Reardon *et al.*, 2006; Monobrullah *et al.*, 2007, Prasad *et al.*, 2008). However, trap catches and weather may not necessarily serve as predictors of the future abundance of certain species in cropping regions (Baker *et al.*, 2010).

3.2.2 Light traps

Insect attraction to light has been exploited for monitoring insect populations with a view to providing early warning of the presence of pests, as well as for many other uses. Light traps have been widely used for monitoring the population dynamics of Lepidoptera and Coleoptera (Wolda, 1992; Watt and Woiwod, 1999; Kato *et al.*, 2000). When compared with other sampling methods, light-trap sampling was found to be more efficient for lepidopteran population dynamics (Raimondo *et al.*, 2004). However, many factors affect catches of insects in light traps (Bowden, 1982). Trap design, the light source and its energy, and the attraction efficiency under certain conditions all contribute to sampling errors. The effects of weather conditions and moonlight on light-trap catches are well documented. For example, trap efficiency for Lepidoptera is positively correlated with temperature and the thickness of cloud cover, and negatively correlated with wind speed, precipitation and the fullness of the moon on the trap night (Bowden, 1982; Dent and Pawar, 1988; Yela and Holyoak, 1997; Butler *et al.*, 1999). The effect of weather factors on the abundance or species richness of Coleoptera captured by light traps has been reported (Rodriguez-Del-Bosque, 1998).

Networks of light traps have been used for year-round monitoring of moth species and the data used to assess the magnitude and reasons for seasonal, annual and long-term faunal changes and their population dynamics in Britain (Lewis, 1980) and India (Anon., 2009), and for weekly larval forecasts on cereal crops in Africa (Odiyo, 1979). Light-trap captures have been used to predict the emergence date of adult beetles from overwintering using a degree-day model (Zou *et al.*, 2004) and for prediction of population sizes based on moth catches (Raimondo *et al.*, 2004). Long-term light-trap data is highly useful in studying the seasonal dynamics of pests. For example, regression analyses have indicated that the spring generation of two species of *Helicoverpa* in eastern cropping zones in Australia could be related to rainfall in putative inland source areas (Zalucki and Furlong, 2005). Light-trap catch data is also useful for validation of simulation model outputs (Reji and Chander, 2008).

3.2.3 Monitoring of migration

Pedgley (1993) discussed and illustrated the role of forecasting and preventive management strategies from a variety of taxa and geographical areas, emphasizing the need to understand the effects of weather on migration. Modelling migration patterns of pests is useful to know their arrival time, identify periods with migration potential in order to time field evaluations, and to provide information on the size of migrating populations. Modelling studies using multi-location long-term suction trap data have indicated that temperature, global radiation and wind speed have a major impact on the flight activity of cereal aphids immigrating on to winter cereal crops during the early autumn and spring seasons (Klueken *et al.*, 2009). A network of light traps along with radars was used for studying the seasonal migration of cotton bollworm (*Helicoverpa armigera* Hübner) (Feng *et al.*, 2009). Furthermore, with automatic systems for monitoring, retrieving and analysing data from remote insect monitoring radars and meteorological equipment, it has been possible to generate daily statistical summaries and graphical representations of the migration activity observed by the radar during the previous night in terms of intensity, altitude, speed and displacement direction of the migrations, as well as the orientation, size and wing-beat frequencies of the migrants, together with the surface weather conditions, at each site. This data was then available over the Internet to users the next day. Such a network has been used in inland eastern Australia since 1999 in studies of the spatial ecology of mobile insect populations and of the utility of migration-monitoring information for operational pest forecasting (Drake *et al.*, 2002). Similarly, analysis of the migration waves of rice brown planthopper (*Nilaparvata lugens* Stål) during June to July into South Korea using the boundary layer atmospheric (BLAYER) model and geographical information system (GIS) explained the spurt in light-trap catch data during late July (Zhu *et al.*, 2000).

3.3 Pest Forecasting

In pest forecasting, several intrinsic attributes of the insects and the determining environmental and host factors need to be considered. Most pest forecast models take into account the phenology of the herbivore and its host. Near real-time pest incidence data coupled with remote sensing and GIS tools facilitate early warning of impending pest build-up in a temporal and spatial perspective. In addition, collection and analysis of weather data from pest-affected areas is an essential input for models. The practical application of model outputs is aided by decision support systems, which are discussed in the following sections.

3.3.1 Considerations in pest forecast research

Accurate forecasting of pest attacks before they actually take place is desired in pest control programmes, so that control measures can be planned with maximum efficiency. Pest dynamics display fluctuations in timing and intensity depending on location and season. Mostly, they tend to fluctuate over a mean level. This average population over time, when computed across several years, results from the sum of action of all positive and negative factors influencing pest populations. Pests of host plants in undisturbed habitats such as forestry have their natural cycles in response to their ecosystem interactions and are most likely to attain equilibrium points in their population levels. Pests of agroecosystems, however, experience rapidly changing environments due to changes in cropping systems and a host of management interventions. As a result, crop pests show a greater degree of instability in population levels. Pests vary in their biology and in their response to their environment. Pests in colder climates in general have discrete generations and resting phases in their life cycles, while in the warmer climates, most species exhibit polymodal patterns of occurrences, with several generations in a year, resulting from continuous breeding opportunities and food availability. On a global scale, seasonal temperatures and rainfall patterns constitute major factors that determine the distributions of organisms (Birch, 1957). Tropical insects generally have the same annual variability as insects from temperate zones, but insect populations from dry areas, such as temperate or tropical regions, tend to fluctuate more than those from wet areas (Wolda, 1978). The effect of environmental stresses such as weather on insect dynamics cannot be explained easily. While environmental stresses such as drought and temperature fluctuations have been recorded preceding insect outbreaks, the precise mode of action of these stresses is unknown (Wallner, 1987).

In nature, pests are regulated by their natural enemies: parasitoids, predators and pathogens, which are in turn influenced by biophysical factors (Hence *et al.*, 2007; Thomson *et al.*, 2010). Therefore, a precise understanding of population dynamics can result from comprehensive ecological studies. However, despite our best efforts, gaps in pest ecological databases remain as a result of the complexity of interactions among the ecosystem components.

Worldwide, one important outcome of understanding population dynamics is to aim for a forecasting capability for appropriate management decisions. Successful forecasting techniques are those that are as simple as possible and that are based on knowledge of the biology and ecology of the pests concerned. In temperate regions, these are basically emergence warnings as the first of the overwintering eggs hatch or the first adults emerge from the overwintering pupae (Collier *et al.*, 1991; Trnka *et al.*, 2007). Because of the climatic regulation, most emergence takes place over a relatively short period of time and is not too difficult to monitor. In the tropical parts of the world, where weather conditions permit continuous breeding of pests most of the time, the warning is generally for the first occurrence of the pest in the crop (Krishnaiah *et al.*, 1997), or sometimes the recording of immigrants from an adjoining area for serious pests with a recorded history of economic damage (Otuka *et al.*, 2005). GIS technology is useful for interpolation of the spatial distribution and spread of crop pests and diseases based on multiple factors including weather conditions (Wu *et al.*, 2008). Quantitative seasonal studies are required over several years to determine seasonal range, variability in numbers and geographical distribution (Hill, 2008). Such studies must use sampling methods appropriate to the pest and its abundance (Cullen *et al.*, 2000), and the seasonal counts should be related to climate and topographical data (Ferguson *et al.*, 2002). By sampling immature stages of insect pests, it is possible to monitor these pests and arrive at approximate estimations of the numbers expected in later stages (Finch, 1989).

Pests that survive on alternative hosts may be sampled so that an estimate of their probable pest density on the main crop can be made. This method has been applied to the peach-potato aphid and the black bean aphid, which are often sampled as overwintering eggs on spindle trees (Leather, 1993). The best spraying date for many Lepidoptera is determined by sampling eggs on the crop. For example, in many parts of Africa, the major cotton bollworms are examined in the field for immature stages (Javaid, 1990).

3.3.2 Insect phenology models

Insects are incapable of internal temperature regulation and hence their development depends on the temperature to which they are exposed. Studies of insect population dynamics often involve modelling growth as a function of ambient temperature. The rate summation methodology has perhaps proved to be the most viable approach to such modelling (Stinner *et al.*, 1974).

The most common development rate model, often called degree-day summation, assumes a linear relationship between development rate and temperature between lower and upper development thresholds (Allen, 1976). This method works well for optimum temperatures (Ikemoto, 2005). The linear model assumes that rates are proportional to temperature, and as amounts are integrals of rates, the amount of development is the integral of the temperature (or a linear function of it) along a time axis and has units of temperature and time (e.g. degree-days). Temperature-dependent development in insects can also be approached using developmental time. The rate of development is traditionally utilized because rate models were created from biochemical and biophysical properties (Sharpe and DeMichele, 1977), although some complications can arise when using rate instead of time (Kramer *et al.*, 1991). Most of the earlier models failed to take into consideration variation between individual insects in their rate of development, which is responsible for the spread of activity of a pest (Regniere, 1984; Phelps *et al.*, 1993). Significant models for modelling the effects of variable temperatures on the development of individual insects within a given population deal with mean rate versus temperature relationships (Wagner *et al.*, 1984a) and distribution of development times (Wagner *et al.*, 1984b, 1985). Instead of treating rate summation as a deterministic quantity, efforts have been made to consider rates as random variables (Stinner *et al.*, 1975). Stochastic approaches to modelling insect development vary in the choice of random variable to be modelled and in the form of the frequency distribution applied to the random variable (Sharpe *et al.*, 1977; Curry *et al.*, 1978). The coefficient of variation of the rate distributions is relatively independent of temperature (Sharpe *et al.*, 1977), indicating that a single temperature-independent distribution of the normalized rate of development adequately describes the distribution at all temperature, which has been validated for 80% of 194 sets of published data on 113 species of insects and mites (Shaffer, 1983). Insect species that exhibit seasonality generally have resting phases – diapause or aestivation – in their life cycles, which can be accommodated in Monte Carlo simulation modelling (Phelps *et al.*, 1993).

As some temperatures are lethal to organisms, it is obvious that development must be a non-linear temperature function at the temperature extremes. Non-linear development rate functions based on enzyme kinetics were developed to describe high-temperature (Johnson and Lewin, 1946) and low-temperature (Hultin, 1955) inhibition, as well as both extremes (Sharpe and DeMichele, 1977). Another non-linear model of temperature-dependent development (Stinner *et al.*, 1974) utilized a function that is a simple sigmoid curve with an inverted relationship when the temperature is above the optimum. This model, as originally given, assumed symmetry about the optimum temperature but can be easily modified for asymmetry. The non-linear model by Logan *et al.* (1976) uses an equation that is asymmetric about the optimum but becomes negative for very high temperatures. Schoolfield *et al.* (1981) modified the model of Sharpe and DeMichele to enhance its overall utility and to simplify parameter estimation. As pointed out by Worner (1992), the interaction of cyclical temperatures with non-linear development can introduce significant deviations from the linear development rate model, especially in the low- and high-temperature regions of the development rate function. Stinner's model gave the best fit for Russian wheat aphid developmental rate data as judged by mean square error and successful convergence when 14 insect developmental models, both deterministic and distributed, were tested (Ma and Bechinski, 2008) using population model design system software developed by Logan and Weber (1989). Ma (2010) applied a survival analysis approach to model development of Russian wheat aphid in relation to temperature and plant growth stages.

Phenology models help predict the time of events in an insect's development and are important analytical tools for predicting, evaluating and understanding the dynamics of pest populations in agro-ecosystems under a variety of environmental conditions. Accurate predictions, however, require accurate recording of the temperatures experienced by the organisms (Morgan, 1991) as well as the duration of development (Danks, 2000).

Degree-day models (Higley *et al.*, 1986) have long been used as part of decision support systems to help growers predict spray timing or when to begin pest scouting (Welch *et al.*, 1978). Phenology models are also used as one component of risk analysis for predicting exotic pest establishment (Baker, 1991; Jarvis and Baker, 2001). A well-known example is the DYMEX modelling package (Su and Fa, 2002; Yonow *et al.*, 2004; Stephens and Dentener, 2005). CLIMEX, although not strictly a phenology model, uses some developmental requirements for risk assessment (Sutherst *et al.*, 1991, 1999, 2000). Another example is the web-based North Carolina State University APHIS Plant Pest Forecast (NAPPFAST) modelling system, which links daily climate and historical weather data with biological models to produce customized risk maps for phytosanitary risk assessments (Borchert and Magarey, 2005). Resources like the *Crop Protection Compendium* (CAB International, 2004) offer insect development summaries, while the University of California Statewide IPM programme lists development data for insects on their website (http://www.ipm.ucdavis.edu/MODELS) for use in degree-day models. An Insect Development Database containing the developmental requirements for over 500 insect species has been created (Nietschke *et al.*, 2007). Insect Life Cycle Modeling (ILCYM) software, a generic open-source computer-aided tool, facilitates the development of phenology models and prediction of pest activity in specific agroecologies (Sporleder *et al.*, 2009).

3.3.3 Life tables and population models

Ecological life tables are one of the tools most useful in the study of population dynamics of insects having discrete generations. Such tables record a series of sequential measurements that reveal population changes throughout the life cycle of a species in its natural environment. Conventionally, a life table is a systematic tabular presentation of survival and mortality in a population for a known cohort of individuals (Morris and Miller, 1954). Long-term data from carefully planned population studies in which all the relevant factors have been measured accurately are important for constructing population models that adequately relate to biological reality. The goal of life-table analysis is to develop a population model that mimics reality. Apart from generating population estimates, this analysis is best done by careful identification and measurement of the independent factors causing mortality such as parasitoids, predators, pathogens and weather factors.

From the life-table studies, it is possible to identify the key factor responsible for increases and decreases in numbers from generation to generation (Morris, 1963; Varley and Gradwell, 1970). A multiple-regression approach involving all the survival components gives greater emphasis to the interaction between different age intervals (Mott, 1967). The equations for different mortalities are combined into a model to predict either the generation-to-generation changes in an insect population density or the average level around which these changes take place. The same analytical approaches used for insects having discrete generations are not applicable to insects with overlapping generations (Varley and Gradwell, 1970). Life table analysis was also utilized to model both the development and survival of the Russian wheat aphid (Ma and Bechinski, 2008). Ecological studies do not often lead to reliable forecasts of the time and size of population peaks because of gaps in the ecological databases such as short-range dispersal, overwintering behaviour, colonization patterns and age-specific mortality including inter- and intraspecific competition (Kogan and Turnipseed, 1987).

3.3.4 Pest simulation models and decision support systems

Simulation models based on mathematical descriptions of biological data as influenced by the environment are more easily applied across locations and environments. Computer programs or software to run these models facilitate the practical application of these models in understanding population dynamics and dissemination of pest forecasts for timely pest management decisions (Coulson and Saunders, 1987). Simulation approaches offer flexibility for testing, refinement, sensitivity analysis as well as field validation of developed models over a wide range of environmental conditions. Thorough descriptions of cropping systems being managed or studied are needed to explain the interactions among pests, plants and the environment (Colbach, 2010). Systems models or other prediction schemes can be used with appropriate biological, environmental, economic or other inputs to analyse the most effective management actions, based on acceptable control, sustainability and assessment of economic or other risks (Strand, 2000).

In an effort to improve *Helicoverpa* management in Australia, a comprehensive population dynamics model (HEAPS: HElicoverpa Armigera and Punctigera Simulation) has been developed, which incorporates the spatial structure of the habitat and pest population and explicitly simulates the adult movement within a regional cropping system (Fitt *et al.*, 1995). This model incorporates modules based on adult movement, oviposition, development, survival and host phenology, and estimates the population in each unit of a grid (Dillon and Fitt, 1990). The EntomoLOGIC decision tool was derived from the SIRATAC decision support system deployed by the Australian cotton industry from 1976 to 1993 to reduce the risk associated with pest management using chemical pesticides. This was developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) in collaboration with the University of Western Sydney, Australia (Hearn and Bange, 2002). Advances in hand-held computing have resulted in expanding the development of CottonLOGIC for use with Palm OS handhelds for widespread adoption by cotton growers in Australia (Bange *et al.*, 2004).

A suite of predictive computer models called MORPH has been developed at the Horticulture Research International, UK (Phelps *et al.*, 1999), for use in fruit and vegetable crops. Using a multi-generation phenology model, ECAMON, Trnka *et al.* (2007) could explain 70% of the variation in the timing of key developmental stages based on daily weather data. ECAMON simulations correctly predicted the presence/absence of the European corn borer over a study region in the Czech Republic during the 1961–1990 reference period. It helped to explain the sudden increase in maize infestation during the unusually warm periods of 1991–2000 and it also estimates that this potential niche will expand within the next 20–30 years. RICEPEST, a model simulating yield loss due to several rice pests under a range of specific production situations in tropical Asia was developed by the International Rice Research Institute (IRRI) in the Philippines.Validation of the model under field experiments yielded promising results (Willocquet *et al.*, 2002).

Web-based models and decision support systems are becoming popular and in future may become an absolute requirement for local, regional/area-wide and international implementation of IPM systems (Waheed *et al.*, 2003). In the USA and the Netherlands, commercial firms are applying mesoscale modelling techniques to forecast insect development and produce gridded products for regional and on-farm planning and pest management (Strand, 2000).

A decision support system has been developed for forecasting black bean aphid (*Aphis fabae*) outbreaks in fields of spring-sown beans. The system takes into account the regional forecast and additionally information provided by the user on individual characteristics of the field and crop such as field shape, size, plant density and sowing date, which are used to downscale the area forecast to the specific field. The system also contains a module for the aphicides that are cleared for use on spring beans and calculates the economics of application (Knight and Cammell, 1994).

SOPRA is applied as a decision support system for eight major insect pests of fruit orchards on a local and regional scale in Switzerland and southern Germany and has a wide range of possible applications in the alpine valleys and north of the Alps (Samietz *et al.*, 2008). Applying time-varying distributed delay approaches, phenology models were developed driven by solar radiation, air temperature and soil temperature on an hourly basis. On the basis of local weather data, the age structure of the pest populations is simulated and crucial events for management activities are predicted by the SOPRA system. Phenology is directly linked to a detailed decision support system and to extended information about the pest insects, as well as to the registered plant protection products. Through a web interface, the simulation results are made available to consultants and growers (www.sopra.info). SIMLEP is a regional forecasting model used in practice for Colorado potato beetle (*Leptinotarsa decemlineata*) in Germany and Austria on a large scale and in the western part of Poland. The SIMLEP decision support system contributed significantly to the improvement of farmers' control measures for

L. decemlineata (Jorg *et al.*, 2007) and later its use expanded to Slovenia (Kos *et al.*, 2009).

In the mid-1990s, CIPRA (Computer Centre for Agricultural Pest Forecasting) software was conceptualized, developed and implemented to access, in real-time, weather data from a network of automated stations. It allows the user to visualize forecasts for 13 insects, two diseases, two storage disorders in addition to the apple crop phenology. These bioclimatic models, which have been developed, implemented and improved over the last 13 years, vary from a simple degree-days approach based on air temperature to more detailed epidemiological models based on air temperature, relative humidity and duration of leaf wetness. Many field specialists are using these model forecasts along with field pest scouting to provide valuable additional information for decision making in pest management and in apple storage strategies (Bourgeois *et al.*, 2008).

3.3.5 Integration of pest and crop simulation models

Crop system models can be used to generate information on the status of the crop as influenced by the growing environment and pests, and including different management options. In practice, there are few examples of these models that include all the necessary components for practical decision making. However, a more practical approach has been the development of individual crop and pest components that can be analysed at the same time to give information that can improve decisions.

The development of decision support systems for agrotechnology transfer (DSSAT 4 funded by the United States Agency for International Development (USAID)) has allowed the rapid assessment of several agricultural production systems around the world to facilitate decision making at farm and policy levels. The trend in development of crop system models is to go for the modular approach (http://www.icasa.net). The development of stand-alone decision support systems for pest components could lead to their practical use. In developed countries, dynamic websites that include interactive models, GIS-based decision systems, real-time weather and market information are rapidly being developed and made available on the Internet (http://www.effita.net) to give farmers real-time benefit in crop management.

The conventional approaches of using empirical models to quantify yield losses are limited in their scope and application, as these are data specific and insensitive to variable cropping and pest conditions. Crop growth models provide a physiologically based approach to simulate pest damage and crop interactions. There have been many efforts to use crop growth models to simulate the effect of pest damage on crop growth and yield by linking the damage effect of pest population levels to the physiological rates and state variables of these models. Insect pests and crop modelling has been discussed in detail by Boote *et al.* (1983) and Coulson and Saunders (1987). A distribution delay model including attrition was applied to simulate population changes in rice leaf-folders. Based on a metabolic pool approach, leaf-folder feeding and hence leaf mass losses to the rice plant were described with a generalized functional response model, which is 'source' and 'sink' driven (Graf *et al.*, 1992). Furthermore, this model stresses the influence of adult migration and natural enemies on leaf-folder population dynamics, both of which are significant and poorly investigated aspects of the leaf-folder life cycle. Later, a generic approach to simulate the damage effects of single or multiple pests was attempted using crop growth models such as CERES-Rice (which is a part of the DSSAT) in the Philippines (Pinnschmidt *et al.*, 1995) and InfoCrop in India (Chander *et al.*, 2007; Reji *et al.*, 2008; Yadav and Chander, 2010). Pest damage levels from field scouting reports can be entered and damage is applied to appropriate physiological coupling points within the crop growth model including leaf area index, stand density, intercepted light, photosynthesis, assimilate amount and translocation rate, growth of different plant organs and leaf senescence. Equations and algorithms were developed to describe competition among multiple pests and to link the computed total damage to the corresponding variables in the crop models. These approaches provide a basis to explore dynamic pest and crop interactions in determining pest management strategies that minimize yield losses.

3.3.6 Remote sensing for pest monitoring and forecasting

Remote sensing techniques are useful in detecting crop stresses such as nutrient deficiency, pest infestation, disease development and to monitor drought. Plants may respond to pest and disease stress in a number of ways, including leaf curling, wilting, chlorosis or necrosis of photosynthetic plant parts, stunted growth and, in some cases, a reduction in leaf area due to severe defoliation. While many of these responses are difficult to quantify visually with acceptable levels of accuracy, precision and speed, these same plant responses will also affect the amount and quality of electromagnetic radiation reflected from plant canopies. The basic premise here is that healthy plants give a higher reflectance in the near-infrared region and a lower one in the visible region, while the opposite is the situation in the case of diseased plants (Teng and Close, 1977). Thus, remote sensing instruments that measure and record changes in electromagnetic radiation may provide a better means of objectively quantifying biotic stresses than visual assessment methods. Additionally, remote sensing can be used repeatedly to collect sample measurements non-destructively and non-invasively (Nilsson, 1995; Yang *et al.*, 2004).

Recent advancements in the field of remote sensing provide ample scope to use this technology for pest monitoring and detection (Prabhakar *et al.*, 2012). Riley (1989) provided an exhaustive review on the use of remote sensing in entomology. Pest damage was associated with spectral indices based on leaf pigments (Riedell and Blackmer, 1999; Yang and Cheng, 2001; Prabhakar *et al.*, 2006, 2011). Optical and video imaging in near-infrared and microwave regions were used to quantify the nocturnal flight behaviour of *H. armigera* (Riley *et al.*, 1992). Fitzgerald (2000) demonstrated that multispectral remote sensing (MRS) would allow farmers to detect early infestation of mites in large-scale cotton fields due to colour shifts and changes in canopy appearance over time. Areas identified on the map could be located with the help of portable GPS equipment by field scouts to verify the mite populations in these areas and recommend regions in the field that require pesticide application.

Remote sensing improves spatial and temporal resolution compared with traditional methods for pest monitoring based on environmental changes (Bhattacharya *et al.*, 2007; Jiang *et al.*, 2008; Dutta *et al.*, 2008). However, the major limitation in use of satellite-borne data in pest forewarning is the timely availability of cloud-free data with the desired spatial and spectral resolution. Better standardization of aerial imagery and accounting for perturbing environmental factors will be necessary to make remote sensing techniques applicable to early pest detection (Luedeling *et al.*, 2009). In addition, the acquisition of airborne data is limited to few high-value crops because of the high costs involved.

3.3.7 Agromet networks for operational pest forecasting

Farmers are mainly interested in current disease and pest severity data, preferably for their localities to aid their decision making in crop protection. Pest monitoring data along with complementary weather data is crucial to run pest forecast models and provide forecasts for operational use. Weather measurements under field conditions from several geo-referenced sites in the crop-cultivated regions additionally provides spatial information that can be used for generating pest forecast maps

(Huang *et al.*, 2008). In Bayern (Germany), a measuring network of 116 field weather stations is used to estimate the development of pests in relation to weather requirements based on forecast models and computer-based decision support systems for near real-time dissemination to farmers (Tischner, 2000). The results of crop- and horticulture-specific models and decision support systems are supplemented by field-monitoring data, which then serve as the main input for the warning services and are disseminated cost-effectively through the Internet (Bugiani *et al.*, 1996; Jorg, 2000). A computerized national forecasting network in apple orchards transmits data from the field to system headquarters automatically. The national forecasting network in Turkey has been expanded and covered apple orchards in 34 provinces in 2006, using 115 electronic forecasting and warning stations (Atlamaz *et al.*, 2007).

3.4 Conclusions

Pest monitoring is the foundation for the issue of early warnings, development and validation of pest forecast models and decision support systems, which are crucial for the design and implementation of successful IPM programmes. Models are potential tools for synthesizing the available information and knowledge on population dynamics of pests in agroecosystems and natural habitats. The development of long-term monitoring spatial data on crop–pest–weather relationships will narrow the gaps in knowledge required for reliable forecasts. Computer-based systems have increased the speed and accuracy of forecasting, and decreasing its costs. Recent developments in information and communication technology offer great scope for wide dissemination and use of pest forecasts. In the tropics, agroecosystems are characterized by greater crop diversity in small parcels of land with dynamically changing weather. Available generic simulation models need to be validated with location-specific inputs for greater accuracy. In developing countries, there is a strong need to establish agro-meteorological networks for specific crop sectors with the major objective of pest forecasting through models and decision support systems.

References

Allen, I.C. (1976) A modified sine wave method for calculating degree days. *Environmental Entomology* 5, 388–396.

Anon. (2009) *Progress Report, 2008*, Vol. 2, *Crop Protection (Entomology, Plant Pathology).* All India Coordinated Rice Improvement Programme (ICAR), Directorate of Rice Research, Hyderabad, India.

Arn, H., Brauchli, J., Koch, U.T., Pop, L. and Rauscher, S. (1997) The need for standards in pheromone technology. *IOBC/WPRS Bulletin* 20, 27–34.

Atlamaz, A., Zeki, C. and Uludag, A. (2007) The importance of forecasting and warning systems in implementation of integrated pest management in apple orchards in Turkey. *EPPO Bulletin* 37, 295–299.

Ayalew, G., Sciarretta, A., Baumgartner, J., Ogol, C. and Lohr, B. (2008) Spatial distribution of diamondback moth, *Plutella xylostella* L. (Lepidoptera: Plutellidae), at the field and the regional level in Ethiopia. *International Journal of Pest Management* 54, 31–38.

Baker, C.R.B. (1991) The validation and use of a life-cycle simulation model for risk assessment of insect pests. *EPPO Bulletin* 21, 615–622.

Baker, G.H., Tann, C.R. and Fitt, G.P. (2010) A tale of two trapping methods: *Helicoverpa* spp. (Lepidoptera, Noctuidae) in pheromone and light traps in Australian cotton production systems. *Bulletin of Entomological Research* 27, 1–15.

Bange, M.P., Deutscher, S.A., Larsen, D., Linsley, D. and Whiteside, S. (2004) A handheld decision support system to facilitate improved insect pest management in Australian cotton systems. *Computers and Electronics in Agriculture* 43, 131–147.

Bhattacharya, B.K., Dutta, S., Dadhwal, V.K., Parihar, J.S., Chattopadhyay, C., Agrawal, R., Kumar, V., Khan, S.A., Roy, S. and Shekhar, C. (2007) Predicting aphid (*Lipaphis erysimi*) growth in oilseed brassica using near surface meteorological data from NOAA TOVS – a case study. *International Journal of Remote Sensing* 28, 3759–3773.

Birch, L.C. (1957) The role of weather in determining the distribution and abundance of animals. *Cold Spring Harbor Symposia On Quantitative Biology* 22, 203–18.

Boote, K.J., Jones, J.W., Mishoe, J.W. and Berger, R.D. (1983) Coupling pests to crop growth simulators to predict yield reductions. *Phytopathology* 73, 1581–1587.

Borchert, D.M. and Magarey, R.D. (2005) A guide to the use of NAPPFAST. <http://www.nappfast.org/usermanual/nappfast-manual.pdf>.

Bourgeois, G., Plouffe, D., Chouinard, G., Beaudry, N., Choquette, D., Carisse, O. and DeEll, J. (2008) The apple CIPRA network in Canada: using real-time weather information to forecast apple phenology, insects, diseases and physiological disorders. *Acta Horticulturae* 803, 29–34.

Bowden, J. (1982) An analysis of factors affecting catches of insects in light traps. *Bulletin of Entomological Research* 72, 535–556.

Bugiani, R., Tiso, R., Butturini, A., Govoni, P. and Ponti, I. (1996) Forecasting models and warning services in Emilia-Romagna (Italy). *EPPO Bulletin* 26, 595–603.

Butler, L., Kondo, C., Barrows, E.M. and Townsend, E.C. (1999) Effects of weather conditions and trap types on sampling for richness and abundance of forest macrolepidoptera. *Environmental Entomology* 28, 795–811.

CAB International (2004) *Crop Protection Compendium*. CAB International, Wallingford, UK.

Cannon, R.J.C., Koerper, D. and Ashby, S. (2004) Gypsy moth, *Lymantria dispar*, outbreak in northeast London, 1995–2003. *International Journal of Pest Management* 50, 259–273.

Chander, S., Kalra, N. and Aggarwal, P.K. (2007) Development and application of crop growth simulation modelling in pest management. *Outlook on Agriculture* 36, 63–70.

Colbach, N. (2010) Modelling cropping system effects on crop pest dynamics: how to compromise between process analysis and decision aid. *Plant Science* 179, 1–13.

Collier, R.H., Finch, S. and Phelps, K. (1991) A simulation model for forecasting the timing of attack of *Delia radicum* on cruciferous crops. *EPBO Bulletin* 21, 419–424.

Coulson, R.N. and Saunders, M.C. (1987) Computer-assisted decision making as applied to entomology. *Annual Review of Entomology* 32, 415–437.

Crummay, F.A. and Atkinson, B.W. (1997) Atmospheric influences on light-trap catches of the brown planthopper rice pest. *Agricultural and Forest Meteorology* 88, 181–197.

Cullen, E.M, Zalom, F.G., Flint, M.L. and Zilbert, E.E. (2000) Quantifying trade-offs between pest sampling time and precision in commercial IPM sampling programs. *Agricultural Systems* 66, 99–113.

Curry, G.L., Feldman, R.M. and Smith, K.C. (1978) A stochastic model for a temperature-dependent population. *Theortical Population Biology* 13, 197–213.

Danks, H.V. (2000) Measuring and reporting life cycle duration in insects and arachnids. *European Journal of Entomology* 97, 285–303.

Dent, D.R. and Pawar, C.S. (1988) The influence of moonlight and weather on catches of *Helicoverpa armigera* (Hübner) (Lepidoptera, Noctuidae) in light and pheromone traps. *Bulletin of Entomological Research* 78, 365–377.

Dillon, M.L. and Fitt, G.P. (1990) HEAPS: a regional model of *Heliothis* population dynamics. In: *Proceedings of the Fifth Australian Cotton Conference*, 8–9 August, Broadbeach, Queensland, Australia. Australian Cotton Grower's Research Association, Australia, pp. 337–344.

Drake, V.A., Wang, H.K. and Harman, I.T. (2002) Insect monitoring radar: remote and network operation. *Computers and Electronics in Agriculture* 35, 77–94.

Dutta, S., Bhttacharya, B.K., Rajak, D.R., Chattopadhyay, C., Dadhwal, V.K., Patel, N.K., Parmar, J.S. and Verma, R.S. (2008) Modeling regional level spatial distribution of aphid (*Lipaphis erysimi*) growth in Indian mustard using satellite-based remote sensing data. *International Journal of Pest Management* 54, 51–62.

El-Sayed, A.M., Suckling, D.M., Wearing, C.H. and Byers, J.A. (2006) Potential of mass trapping for long-term pest management and eradication of invasive species. *Journal of Economic Entomology* 99, 1550–1564.

Fadamiro, H.Y. (2004) Pest phenology and evaluation of traps and pheromone lures for monitoring flight activity of oblique banded leaf roller (Lepidoptera: Tortricidae) in Minnesota apple orchards. *Journal of Economic Entomology* 97, 530–538.

Feng, H., Wu, X., Wu, B. and Wu, K. (2009) Seasonal migration of *Helicoverpa armigera* (Lepidoptera: Noctuidae) over the Bohai Sea. *Journal of Economic Entomology* 102, 95–104.

Ferguson, A.W., Klukowski, Z., Walczak, B., Clark, S.J., Mugglestone, M.A., Perry, J.N. and Williams, I.H. (2002) Spatial distribution of pest insects in oilseed rape: implications for integrated pest management. *Agricuture, Ecosystems and Environment* 95, 509–521.

Finch, S. (1989) Ecological consideration in the management of *Delia* pest species in vegetable crops. *Annual Review of Entomolgy* 34, 117–137.

Fitt, G.P., Dillon, M.L. and Hamilton, J.G. (1995) Spatial dynamics of *Helicoverpa* populations in Australia: simulation modeling and empirical studies of adult movement. *Computers and Electronics in Agriculture* 13, 177–192.

Fitzgerald, G. (2000) Bug checking for mites – from the sky. *Australian Cottongrower* 21, 29–31.

Gallardo, A., Ocete, R., Lopez, M.A., Maistrello, L., Ortega, F., Semedo, A. and Soria, F.J. (2009) Forecasting the flight activity of *Lobesia botrana* (Denis and Schiffermüller) (Lepidoptera, Tortricidae) in Southwestern Spain. *Journal of Applied Entomology* 133, 626–632.

Graf, B., Lamb, R., Heong, K.L. and Fabellar, L. (1992) A simulation model for the population dynamics of rice leaf folders (Lepidoptera: Pyralidae) and their interactions with rice. *Journal of Applied Ecology* 29, 558–570.

Gurrero, A. and Reddy, G.V.P. (2001) Optimum timing of insecticide applications against diamondback moth *Plutella xylostella* in cole crops using threshold catches in sex pheromone traps. *Pest Management Science* 57, 90–94.

Gwadi, K.W., Dike, M.C. and Amatobi, C.I. (2006) Seasonal trend of flight activity of the pearl millet stemborer, *Coniesta ignefusalis* (Lepidoptera: Pyralidae) as indicated by pheromone trap catches and its relationship with weather factors at Samara, Nigeria. *International Journal of Tropical Insect Science* 26, 41–47.

Hearn, A.B. and Bange, M.P. (2002) SIRATAC and CottonLOGIC: persevering with DSSs in the Australian cotton industry. *Agricultural Systems* 74, 27–56.

Hence, T., van Baaren, J., Vernon, P. and Boivin, G. (2007) Impact of extreme temperature on parasitoids in climate change perspective. *Annual Review of Entomology* 52, 107–126.

Higley, L.G., Pedigo, L.P. and Ostlie, K.R. (1986) DEGDAY: a program for calculating degree-days, and assumptions behind the degree-day approach. *Environmental Entomology* 15, 999–1016.

Hill, D.S. (2008) Pests of crops in warmer climates and their control. Springer.

Hirao, T.M., Murakami, M. and Kashizaki, A. (2008) Effects of mobility on daily attraction to light traps: comparison between lepidopteran and coleopteran communities. *Insect Conservation and Diversity* 1, 32–39.

Hopkinson, R.F. and Soroka, J.J. (2010) Air trajectory model applied to an in-depth diagnosis of potential diamondback moth infestations on the Canadian prairies. *Agricultural and Forest Meteorology* 150, 1–11.

Huang, Y., Lan, Y., Westbrook, J.K. and Hoffmann, W.C. (2008) Remote sensing and GIS applications for precision area-wide pest management: implications for homeland security. *GeoJournal Library* 94, 241–255.

Hultin, E. (1955) Influence of temperature on the rate of enzymatic processes. *Acta Chemica Scandinavica* 9, 1700.

Ikemoto, T. (2005) Intrinsic optimum temperature for development of insects and mites. *Environmental Entomology* 34, 1377–1387.

Isaacs, R. and van Timmeren, S. (2009) Monitoring and temperature-based prediction of the whitemarked tussock moth (Lepidoptera: Lymantridae) in blueberry. *Journal of Economic Entomology* 102 , 637–645.

Jarvis, C.H. and Baker, R.H.A. (2001) Risk assessment for nonindigenous pests, I. Mapping the outputs of phenology models to assess the likelihood of establishment. *Diversity Distribution* 7, 223–235.

Javaid, I. (1990) Application of insecticides in Zambia: timing of spray application. *International Journal of Pest Management* 36, 1–9.

Jiang, J.A., Tseng, C.L., Lu, F.M., Yang, E.C., Wu, Z.S., Chen, C.P., Lin, S.H., Lin, K.C. and Liao, C.S. (2008) A GSM-based remote wireless automatic monitoring system for field information: a case study for ecological monitoring of the oriental fruit fly, *Bactrocera dorsalis* (Hendel). *Computers and Electronics in Agriculture* 62, 243–259.

Johnson, F.H. and Lewin, I. (1946) The growth rate of *E. coli* in relation to temperature, quinine and coenzyme. *Journal of Cellular and Comparative Physiology* 28, 47–75.

Jorg, E. (2000) Structure and organization of warning services in Rheinland-Pfalz (Germany). *EPPO Bulletin* 30, 31–35.

Jorg, E., Racca, P., Preib, U., Butturini, A., Schmiedl, J. and Wojtowicz, A. (2007) Control of Colorado potato beetle with the SIMLEP decision support system. *EPPO Bulletin* 37, 353–358.

Kato, M., Itioka, T., Sakai, S., Momose, K., Yamane, S., Hamid, A.A. and Inoue, T. (2000) Various population fluctuation patterns of light-attracted beetles in a tropical lowland dipterocarp forest in Sarawak. *Population Ecology* 42, 97–104.

Klueken, A.M., Hau, B., Ulber, B. and Poehling, H.M. (2009) Forecasting migration of cereal aphids (Hemiptera: Aphididae) in autumn and spring. *Journal of Applied Entomology* 133, 328–344.

Knight, J.D. and Cammell, M.E. (1994) A decision support system for forecasting infestations of the black bean aphid, *Aphis fabae* Scop., on spring-sown field beans, *Vicia faba*. *Computer and Electronics in Agriculture* 10, 269–279.

Knutson, A.E. and Muegge, M.A. (2010) A degree-day model initiated by pheromone trap captures for managing pecan nut casebearer (Lepidoptera: Pyralidae) in pecans. *Journal of Economic Entomology* 103, 735–743.

Kogan, M. and Turnipseed, S.G. (1987) Ecology and management of soybean arthropods. *Annual Review of Entomology* 32, 507–538.

Kos, K., Tschope, B., Jorg, E. and Trdan, S. (2009) Testing the suitability of SIMLEP decision support system for protection of potato against Colorado potato beetle (*Leptinotarsa decemlineata* [Say], Coleoptera, Chrysomelidae) in Slovenia. *Acta Agriculturae Slovenica* 93, 93–104.

Kramer, D.A., Stinner, R.E. and Hain, F.P. (1991) Time versus rate in parameter estimation of nonlinear temperature-dependent development models. *Environmental Entomology* 20, 484–488.

Krishnaiah, N.V., Pasalu, I.C., Padmavathi, L., Krishnaiah, K. and Ram Prasad, A.S.R. (1997) Day degree requirement of rice yellow stem borer, *Scirpophaga incertulas* (Walker). *Oryza* 34, 185–186.

Leather, S.R. (1993) Overwintering in six arable aphid pests: a review with particular relevance to pest management. *Journal of Applied Entomology* 116, 217–233.

Lewis, T. (1980) Britain's pest monitoring network for aphids and moths. *EPPO Bulletin* 10 , 39–46.

Lewis, T. (1981) Pest monitoring to aid insecticide use. *Philosophical Transactions of the Royal Society B: Biological Sciences* 295, 153–162.

Liebhold, A.M. and Tobin, P.C. (2008) Population ecology of insect invasions and their management. *Annual Review of Entomology* 53, 387–408.

Logan, J.A. and Weber, L.A. (1989) *Population Model Design System (PMDS): User's Guide*. Department of Entomology, Virginia Polytechnic Institute and State University, Blackburg, Virginia.

Logan, J.A., Wollkind, D.T., Hoyt, J.C. and Tanigoshi, L.K. (1976) An analytic model for description of temperature dependent rate phenomena in arthropods. *Environmental Entomology* 5, 1130–1140.

Luedeling, E., Hale, A., Zhang, M., Bentley, W.J. and Dharmasri, L.C. (2009) Remote sensing of spider mite damage in California peach orchards. *International Journal of Applied Earth Observation and Geoinformation* 11, 244–255.

Ma, Z.S. (2010) Survival analysis approach to insect life table analysis and hypothesis testing: with particular reference to Russian wheat aphid (*Diuraphis noxia* (Mordvilko)) populations. *Bulletin of Entomological Research* 100, 315–324.

Ma, Z.S. and Bechinski, E.J. (2008) A survival-analysis-based simulation model for Russian wheat aphid population dynamics. *Ecological Modelling* 216, 323–332.

Merril, S.C., Gebre-Amlak, A., Armstrong, J.S. and Pearirs, F.B. (2010) Nonlinear degree-day models of the sunflower weevil (Curculionidae: Coleoptera). *Journal of Economic Entomology* 103, 303–307.

Monobrullah, M., Bharti, P., Shankar, U., Gupta, R.K., Srivastava, K. and Ahmad, H. (2007) Trap catches and seasonal incidence of *Spodoptera litura* on cauliflower and tomato. *Annals of Plant Protection Sciences* 15, 73–76.

Morgan, D. (1991) The sensitivity of simulation models to temperature changes. *EPPO Bulletin* 21, 393–397.

Morris, R.F. and Miller, C.A. (1954) The development of life tables for the spruce budworm. *Canadian Journal of Zoology* 32, 283–301.

Morris, R.F. (ed.) (1963) The dynamics of epidemic spruce budworm populations. *Memoirs of the Entomological Society of Canada* 31, 332.

Mott, D.G. (1967) The analysis of determination in population systems. *Systems Analysis in Ecology* 7, 179–194.

Nietschke, B.S., Magarey, R.D., Borchert, D.M., Calvin, D.D. and Jones, E. (2007) A developmental database to support insect phenology models. *Crop Protection* 26, 1444–1448.

Nilsson, H.E. (1995) Remote sensing and image analysis in plant pathology. *Annual Review of Phytopathology* 15, 489–527.

Odiyo, P.O. (1979) Forecasting infestations of a migrant pest: the African armyworm *Spodoptera exempta* (Walk.). *Philosophical Transactions of the Royal Society B: Biological Sciences* 287, 403–413.

Otuka, A., Watanabe, T., Suzuki, Y., Matsumura, M., Furuno, A. and Chino, M. (2005) Real-time prediction system for migration of rice planthoppers *Sogatella furcifera* (Horváth) and *Nilaparvata lugens* (Stål) (Homoptera: Delphacidae). *Applied Entomology and Zoology* 40, 221–229.

Pathak, M.D. (1968) Ecology of common insect pests of rice. *Annual Review of Entomology* 13, 257–294.

Pedgley, D.E. (1993) Managing migratory insect pests – a review. *International Journal of Pest Management* 39, 3–12.

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 Protection* 12, 335–341.

Phelps, K., Reader, R.J. and Hinde, C.J. (1999) HIPPO – flexible software for the construction, integration and distribution of biologically realistic models. *Aspects of Applied Biology* 55, 81–88.

Pinnschmidt, H.O., Batchelor, W.D. and Teng, P.S. (1995) Simulation of multiple species pest damage in rice using CERES-Rice. *Agricultural Systems* 48, 193–222.

Prabhakar, M., Prasad, Y.G., Mandal, U.K., Ramakrishna, Y.S., Ramalakshmiaih, C., Venkateswarlu, N.C. and Subrmanyam, K. (2006) Spectral characteristics of peanut crop infected by late leaf spot disease under rainfed conditions. *Proceedings of SPIE* 6411, 641101.

Prabhakar, M., Prasad, Y.G., Thirupathi, M., Sreedevi, G., Dharajothi, N. and Venkateswarlu, B. (2011) Use of groundbased hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). *Computers and Electronics in Agriculture* 79, 189–198.

Prabhakar, M., Prasad, Y.G. and Rao, M.N. (2012) Remote sensing of biotic stress in crop plants and its application for pest management. In: Venkateswarlu, B. *et al*., (eds) *Crop Stress and its Management*. Springer Science, Dordrecht, pp. 517–545.

Prasad, N.V.V.S.D., Mahalakshmi, M.S. and Rao, N.H.P. (2008) Monitoring of cotton bollworms through pheromone traps and impact of abiotic factors on trap catch. *Journal of Entomological Research* 32, 187–192.

Raimondo, S., Strazanac, J.S. and Butler, L. (2004) Comparison of sampling techniques used in studying Lepidoptera population dynamics. *Environmental Entomology* 33, 418–425.

Reardon, B.J., Sumerford, D.V. and Sappington, T.W. (2006) Impact of trap design, windbreaks, and weather on captures of European corn borer (Lepidoptera: Crambidae) in pheromone-baited traps. *Journal of Economic Entomology* 99, 2002–2009.

Regniere, J. (1984) A method of describing and using variability in development rates for the simulation of insect phenology. *Canadian Entomologist* 116, 1367–1376.

Reji, G. and Chander, S. (2008) A degree-day simulation model for the population dynamics of the rice bug, *Leptocorisa acuta* (Thunb.). *Journal of Applied Entomology* 132, 646–653.

Reji, G., Chander, S. and Aggawal, P.K. (2008) Simulating rice stem borer, *Scirpophaga incertulas* Wlk., damage for developing decision support tools. *Crop Protection* 27, 1194–1199.

Riedell, W.E. and Blackmer, T.M. (1999) Leaf reflectance spectra of cereal aphid damaged wheat. *Crop Science* 39, 1835–1840.

Riley, J.R. (1989) Remote sensing in entomology. *Annual Review of Entomology* 34, 247–271.

Riley, J.R., Armes, N.J., Reynolds, D.R. and Smith, A.D. (1992) Nocturnal observations on flight behaviour of *Helicoverpa armigera* (Lepidoptera: Noctuidae) in the post-rainy season in central India. *Bulletin of Entomological Research* 82, 243–256.

Rodriguez-Del-Bosque, L.A. (1998) A sixteen-year study on the bivoltinism of *Anomala favipennis* (Coleoptera, Chrysomelidae) in Northern Mexico. *Environmental Entomology* 23, 1409–1415.

Samietz, J., Graf, B., Höhn, H., Höpli, H.U. and Schaub, L. (2008). SOPRA: phenology modelling of major orchard pests – from biological basics to decision support. *Acta Horticulturae* 803, 35–42.

Schoolfield, R.M., Sharpe, P.J. and Magnuson, C.E. (1981) Nonlinear regression of biological temperature-dependent rate models based on absolute reaction-rate theory. *Journal of Theoretical Biology* 88, 719–731.

Shaffer, P.L. (1983) Prediction of variation in development period of insects and mites reared at constant temperatures. *Environmental Entomology* 12, 1012–1019.

Sharpe, J.H. and DeMichele, D.W. (1977) Reaction kinetics of poikilotherm development. *Journal of Theoretical Biology* 64, 649–670.

Sharpe, P.J.H., Curry, G.L., DeMichele, D.W. and Coel, C.L. (1977) Distribution model of organism development times. *Journal of Theoretical Biology* 66, 21–28.

Spear-O'Mara, J. and Allen, D.C. (2007) Monitoring populations of saddled prominent (Lepidoptera: Notodontidae) with pheromone-baited traps. *Journal of Economic Entomology* 100, 335–342.

Sporleder, M., Simon, R., Gonzales, J. Chavez, D., Juarez, H., De Mendiburu, F. and Krosche, J. (2009) *ILCYM – Insect Life Cycle Modelling: a Software Package for Developing Temperature Based Insect Phenology Models with Applications for Regional and Global Risk Assessments and Mapping*. International Potato Centre, Lima, Peru.

Stephens, A.E.A. and Dentener, P.R. (2005) *Thrips palmi* – potential survival and population growth in New Zealand. *New Zealand Plant Protection* 58, 24–30.

Stinner, R.E., Gutierrez, A.P. and Butler, G.D. Jr. (1974) An algorithm for temperature-dependent growth rate simulation. *Canadian Entomologist* 106, 519–524.

Stinner, R.E., Butler, G.D., Bachelor, J.S. and Tuttle, C. (1975) Simulation of temperature dependent development in population dynamics models. *Canadian Entomologist* 107, 1167–1174.

Strand, J.F. (2000) Some agrometeorological aspects of pest and disease management for the 21st century. *Agricultural and Forest Meteorology* 103, 73–82.

Su, J.W. and Fa, S.C. (2002) Trapping effect of synthetic pheromone blends on two stem borers *Chilo syppressalis* and *Scirpophaga incertulas*. *Chinese Rice Research Newsletter* 10, 8–9.

Sutherst, R.W., Maywald, G.F. and Bottomley, W. (1991) From CLIMEX to PESKY, a generic expert system for pest risk assessment. *Bull. OEPP* 21, 595–608.

Sutherst, R.W., Maywald, G.F., Yonow, T. and Stevens, P.M. (1999) *CLIMEX: Predicting the Effects of Climate on Plants and Animals*. CSIRO Publishing, Collingwood, Australia.

Sutherst, R.W., Maywald, G.F. and Russell, B.L. (2000) Estimating vulnerability under global change: modular modelling of pests. *Agriculture, Ecosystems and Environment* 82, 303–319.

Teng, P.S. and Close, R.C. (1977) Spectral reflectance of healthy and leaf rust infected barley leaves. *Australian Plant Pathology Society Newsletter* 6, 7–9.

Thomson, L.J., Macfadyen, S. and Hoffman, A.A. (2010) Predicting the effect of climate change on natural enemies of agricultural pests. *Biological Control* 52, 296–306.

Tischner, H. (2000) Instruments of the warning service for plant protection in Bayern (Germany). *EPPO Bulletin* 30, 103–104.

Trnka, M., Muska, F., Semeradvoa, D., Dubrovsky, M., Kocmankova, E. and Zalud, Z. (2007) European corn borer life stage model: regional estimates of pest development and spatial distribution under present and future climate. *Ecological Modelling* 207, 61–84.

Varley, G.C. and Gradwell, G.R. (1970) Recent advances in insect population dynamics. *Annual Review of Entomology* 15, 1–24.

Wagner, T.L., Wu, H.I., Sharpe, P.J.H., Schoolfield, R.M. and Coulson, R.N. (1984a) Modelling insect development rates: a literature review application of a biophysical model, *Annals of the Entomological Society of America* 77, 208–225.

Wagner, T.L., Wu, H.I., Sharpe, P.J.H. and Coulson, R.N. (1984b) Modeling distributions of insect development time: a literature review and application of the Weibull function. *Annals of the Entomological Society of America* 77, 475–487.

Wagner, T.L., Wu, H.I., Feldman, R.M., Sharpe, P.J.H. and Coulson, R.N. (1985) Multiple-cohort approach for simulating development of insect populations under variable temperatures. *Annals of the Entomological Society of America* 78, 691–704.

Waheed, I.B., Leonard, C. and Kogan, M. (2003) Integrated pest management and internet-based delivery systems. *Neotropical Entomology* 32, 373–383.

Wall, C., Garthwaite, D.G., Blood Smyth, J.A. and Sherwood, A. (1987) The efficacy of sex-attractant monitoring for the pea moth, *Cydia nigricana*, in England, 1980–1985. *Annals of Applied Biology* 110, 223–229.

Wallner, W.E. (1987) Factors affecting insect population dynamics: differences between outbreak and non-outbreak species. *Annual Review of Entomology* 32, 317–340.

Watt, A.D. and Woiwod, I.P. (1999) The effects of phenological asynchrony on population dynamics: analysis of fluctuations of British macrolepidopters. *Oikos* 87, 411–416.

Welch, S.M., Croft, B.A. and Michels, M.F. (1978) PETE: an extension phenology modeling for management of muti-species pest complex. *Environmental Entomology* 7, 487–494.

Willocquet, L., Savary, S., Fernandez, L., Elazegui, F.A., Castilla, N., Zhu, D., Tang, Q., Huang, S., Lin, X., Singh, H.M. and Srivastava, R.K. (2002) Structure and validation of RICEPEST, a production situation-driven, crop growth model simulating rice yield response to multiple pest injuries for tropical Asia. *Ecological Modelling* 153, 247–268.

Witzgall, P., Kirsch, P. and Cork, A. (2010) Sex pheromones and their impact on pest management. *Journal of Chemical Ecology* 36, 80–100.

Wolda, H. (1978) Fluctuations in abundance of tropical insects. *American Naturalist* 112, 1017–1045.

Wolda, H. (1992) Trends in abundance of tropical forest insects. *Oecologia* 89, 47–52.

Worner, S.P. (1992) Performance of phenological models under variable temperature regimes: consequences of the Kaufmann or rate summation effect. *Environmental Entomology* 21, 689–699.

Wu, X., Wang, C., Xu, Z. and Hu, Y. (2008) Application of GIS technology in monitoring and warning system for crop diseases and insect pests. *Proceedings of SPIE* 7145, 714516.

Yadav, D.S. and Chander, S. (2010) Simulation of rice plant hopper damage for developing pest management decision support tools. *Crop Protection* 29, 267–276.

Yang, C.M. and Cheng, C.H. (2001) Spectral characteristics of rice plants infested by brown plant hoppers. *Proceedings of the National Science Council Republic of China. Part B: Life Sciences* 25, 180–186.

Yang, Z.M., Rao, N., Elliot, N.C., Kindler, S.D. and Elliott, N.C. (2004) Remote sensing to detect plant stress with particular reference to stress caused by green bug: a review. *South Western Entomologist* 29, 227–236.

Yela, J.L. and Holyoak, M. (1997) Effects of moonlight and meteorological factors on light and bait trap catches of noctuid moths (Lepidoptera: Noctuidae). *Environmental Entomology* 26, 1283–1290.

Yonow, T., Zalucki, M.P, Sutherst, R.W, Dominiak, B.C, Maywald, G.F, Maelzer, D.A and Kriticos, D.J. (2004) Modelling the population dynamics of the Queensland fruit fly, *Bactrocera (Dacus) tryoni*: a cohort-based approach incorporating the effects of weather. *Ecological Modeling* 17, 39–30.

Zalucki, M.P. and Furlong, M.J. (2005) Forecasting *Helicoverpa* populations in Australia: a comparison of regression based models and a bioclimatic based modeling approach. *Insect Science* 12, 45–46.

Zhu, M., Song, Y., Uhm, K.B., Turner, R.W., Lee, J.H. and Roderick, G.K. (2000) Simulation of the long range migration of brown planthopper, *Nilaparvata lugens* (Stål), by using boundary layer atmospheric model and the geographic information system. *Journal of Asia-Pacific Entomology* 3, 25–32.

Zou, L., Stout, M.J. and Ring, D.R. (2004) Degree-day models for emergence and development of the rice water weevil (Coleoptera: Curculionidae) in Southwestern Louisiana. *Environmental Entomology* 33, 1541–1548.