Disease Modeling as a Tool to Assess the Impacts of Climate Variability on Plant Diseases and Health

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Abstract

Biotic stress is one of the major environmental factors that affect the plant's growth and life cycle. Plant pathogens are major constraints and severe threats to agricultural production in changing climate scenarios. The effects of climate variability on plant diseases and pathogens have been examined in various plant pathosystems. Climate change is predicted to affect the development of pathogens, their survival, vigor, sporulation, multiplicity, and host susceptibility that ultimately cause changes in the crop diseases. It also affects the inoculum dispersion and pathogenicity. These effects vary depending on pathosystems and geographic locations. Climate change not only affects optimal conditions of infection but also host specificity and infection mechanism in plants.

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Temperature, light, and humidity are the major factors that control the development and growth of diseases. So, climate change is an emerging challenge that is impacting and driving the plants and pathogens growth, disease development in a pathosystem. This overview is aimed to summarize the previous research, reviews, opinions, and recent trends in studying the effects of climate variability on pathogens and plants health. However, managing and predicting climate change impacts are complicated because of the interaction between the indirect effects and global climate change drivers. Similarly, uncertainty in plant disease development models in changing climate needs the diversification in management strategies. Protection of plants against diseases and pathogens is an essential direction for researchers to make the plants more resistant to pests and diseases. There is a need for further research in different areas under multiple climate-changing factors and scenarios using the disease modeling frameworks such as BIOMA and APSIM-DYMEX.

Keywords

Pathosystems Climate change Biotic stress Disease modeling

12.1 Introduction

Change in the statistical distribution of weather for an extended period of time is called climate change. The end of the twentieth century and the start of the twenty-first century were the warmest periods globally. The availability of information on the effects of climate variability upon plant diseases is very limited. It was documented that plant diseases will be affected by the changing climate like other global change components (Regniere 2011; Bradley et al. 2012). The influence of the environment on plant disease is considered by plant pathologists disease studies, and the disease triangle illustrates the interaction among host plants, environment, and pathogen for disease development (Grulke 2011). Climate variability is one of the ways in which the environment can be suppressive or conducive for disease (Ahmed 2020; Ahmed and Stockle 2016; Perkins et al. 2011; Fuhrer 2003). Therefore plant diseases are indicators of climate variability (Garrett et al. 2015). Since the last decade plant virus distribution and the population is increasing swiftly as well as many new infectious diseases are also identified. Plant diseases are not only accelerated by increased activity of pathogens but also due to declined tolerance in plants as a result of adverse environmental conditions (Huseynova et al. 2014). Anthropogenic activities are the important causes of plant diseases spread; sudden oak death is an example of these activities (Prospero et al. 2009). Climate variability is impacting the plants in agriculture ecosystems globally (Stern 2008). Little work has been carried out on modeling the impacts of climate variability on disease epidemics in plants. However, several tree diseases are emerging because of climate change (Garrett et al. 2006; Garrett et al. 2015). This change is affecting the crops directly as well as indirectly by interacting with microbial pests and resulting in several disease epidemics in plants (Bosch et al. 2007; Chakraborty 2005). A variety of mechanisms can affect the health of plants in changing climates such as acceleration in pathogen evolution, fewer incubation periods, and extreme climatic events (Sutherst et al. 2011). Climate change is impacting the hosts and pathogens directly and indirectly by altering their physiology (Desprez-Loustau et al. 2006; Garbelotto et al. 2010).

12.2 Recently Occurred Changes

Climate variability has been measured, and these changes have been associated with plant pathosystems. Environment and climatic conditions strongly affect the plant diseases in the forests. Pathogens, moisture, temperature, and stress interaction influence the severity of infections and diseases. Climate changes result in the evolvement of more invasive species and increase stress on plants leading to the condition that is favorable for diseases in plants. Changes in temperature, moisture, and precipitation in North America were associated with tree death events (Van Mantgem et al. 2009; Sturrock et al. 2011). In central Europe rise in winter temperature and fluctuations in the rain favored the root rot diseases in forests by supporting infection through *Phytophthora* spp. (Jung 2009). At Oregon coast climatic changes resulted in the Swiss needle epidemic, and a further increase of 0.4 °C in temperature is predicted by 2050 in Pacific Northwest forests that will further increase the severity of the epidemic and increase the outbreak (Stone et al. 2008; Sturrock et al. 2011). In Oregon and California sudden death of Oak trees caused by *Phytophthora ramorum* abruptly increased due to extreme climatic events. Heavy rains and extension of moist weather in warm season favor the infection in plants and lead to the death (Swiecki and Bernhardt 2016; Frankel 2007). In Europe study was carried out for *Phytophthora cinnamomi* in Oak. Results demonstrated that an increase in temperature worsens the root disease (Brasier 1996; Brasier and Scott 1994). A similar study was carried out for eucalyptus (Booth et al. 2000). In Alaska yellow cedar tree's mortality rate is also increasing due to changing climatic conditions. As earlier, melting of snow exposed roots to the cold conditions that result in freezing and cause injury (Thompson 2007).

Several studies were carried out to assess the climate change impacts on plant diseases. Most studies investigated the head blight, leaf rust and blotch in wheat, downy mildew in grapes, and phoma stem canker in oilseed rapes. These studies are mostly carried out in European countries and Brazil (Juroszek and von Tiedemann 2015). However, rice is a major crop in Asian countries, and rice blast is an important disease that results in major losses in rice production. Luo et al. (1995) conducted an analysis of the blast epidemic produced by *Magaporthe grisea*. Results showed that change in rainfall has no impacts, while in subtropical regions, disease severity is increased because of high temperatures. However, the opposite trend was observed in humid areas. An experiment was conducted to study the impacts on soil-borne pathogens. Results showed an increase in damping-off in cotton plants under elevated CO_2 (Ahmad and Hasanuzzaman 2020; Runion et al. 1994). In barley an increase in growth was observed at high CO_2 concentrations but after the infection of powdery mildew, the growth was retarded (Hibberd et al. 1996). The incidence of leaf rust was studied in spring wheat under elevated CO_2 and ozone. The infection rate was inhibited by the ozone; however, ozone damage on leaves was altered by infection and CO_2 (Tiedemann and Firsching 2000). Temperature evaluation can increase the yellow dwarf symptoms in wheat and barley (Mikkelsen et al. 2015). In maize crop, increased CO_2 makes it more prone to *Fusarium* (Vaughan et al. 2014). Fusarium Crown rot diseases in wheat increased with more CO_2 (Melloy et al. 2014) while reduced in elevated temperature (Vary et al. 2015). Increased CO_2 effects were studied on a C_3 *Scirpus olneyi*, and the C_4 grass *Spartina patens*. However, shoot N and water content were also determined. Plants with increased CO_2 levels showed an increase of 37% in resistance while in reduced N and increased water content the disease severity was also enhanced (Thompson and Drake 1994). Similarly, in Finland, climate variability will affect potato production. The risk of potato blight resulted from *Phytophthora infestans* will be increased and a nematode called *Globodera rostochiensis* will also be distributed all over the country because it has the ability to support many generations in a single year (Carter et al. 1996). In tomato plants, climate change will not affect diseases like white mold, late blight, verticillium wilt, septoria leaf spot, and tomato mosaic. But the importance of powdery mildew, early blight, bacterial wilt, and leaf curl will increase (Gioria et al. 2008).

12.3 Climate Change Impacts on Pathogens

The rise in temperature may initiate the growth and development of inactive pathogens (Fig. 12.1). Temperature and rainfall changes may cause alteration in growth, rate of progress, physiology, and resistivity of the host (Chakraborty and Datta 2003). Temperature affects the diseases caused by bacteria like *Acidovorax avenae*, *Ralstonia solanacearum*, and *Burkholderia glumae*. Bacteria can move to the areas where temperature depending diseases are not previously noticed (Kudela 2009). As the rise in temperature reduce winter length, whereas growth and reproduction of pathogens get modified (Ladanyi and Horvath 2010). Researches indicated that wheat and oats are becoming more susceptible to the rust disease due to the increase in temperature and humidity, while resistant has been shown by few forage species to alleviated temperatures (Coakley et al. 1999). In the cold duration of the year, warming can release cold stress but in the hot period of the year, it increases heat stress. Various models have been used for forecasting the epidemics based on the rise in pathogen growth and infection in a specific range of temperatures. Fungi that are causing the disease to plant at cold temperatures experience longer suitable temperature periods for reproduction and growth in a warmer climate. Late blight epidemic became more severe and required more fungicide to control diseases if warm temperature onset earlier. These effects of increased temperature vary throughout the year as increase in temperature in colder parts may reduce plant stress while in hotter parts it results in increase of alleviated

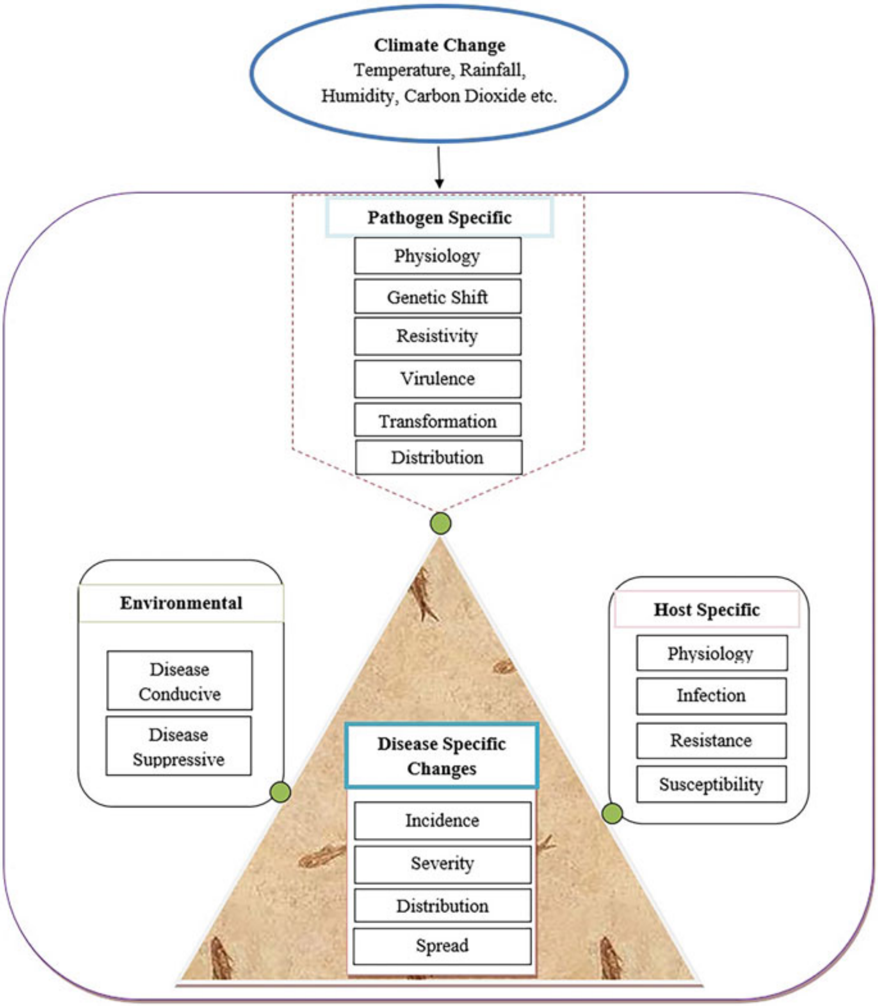


Fig. 12.1 Impacts of climate variability on plant diseases

temperature stress. Lower rainfall decreases the incidence of downy mildew infections in grape plants. Temperature and moisture are corelated and affect the pathogens reproduction (Caffarra et al. 2012) and also affect the populations of pathogens (Legler et al. 2012). When the temperature is higher, the moisture will be reduced and result in reduced risk of disease (Desprez-Loustau et al. 2006). Dense canopies result in more moisture and increase leaf wetness that will favor the growth and development of pathogens.

Alleviated CO_2 impacts both pathogen and host in multiple manners. Under alleviated CO_2 and temperature, new races are evolving very rapidly, and the population of pathogens is boosted as well as infectious cycles are also increasing due to favorable climate in the large canopy (Chakraborty 2013). Higher concentrations of CO_2 lead to the increased production of biomass depending on the availability of nutrients and water, weeds, diseases, and pests damage. However, the increased carbohydrates amount in plant tissues favors the biotrophic fungi, that is, rust (Chakraborty and Datta 2003). Therefore, biomass increase can alter the microclimate of plants and also the chances of infection. More CO_2 will result in slow decomposition of residues that will favor in overwintering of harmful organisms and more fugal spore production will occur. Increased CO_2 can affect the growth of pathogens by leading to higher production of fungal spores but it can also cause some physiological alterations in host plants that enhance the resistance against pathogens (Coakley et al. 1999). At higher concentrations of CO_2 growth of germ tube and germination rate were slower in conidium of *C. gleosprioides* fungi but after infection fungi develop quickly and attain sporulation (Chakraborty et al. 2002). Similarly, higher ozone concentration can increase rust infection on the tree of poplar but it is minimized by increased CO_2 (Karnosky et al. 2002).

12.4 Climate Change Impacts on Plants

Plants show alteration in their gene expression in response to the climatic changes, while transcriptome enables plants to respond to these changes (Garrett et al. 2006). Climate variability directly impacts the plant's biology, physiology, biochemical process, and morphology (Fig. 12.1). These changes affect the pathogens colonization, symptoms expression, colonization infection, etc.

Drought can reduce stomatal activity as well as photosynthesis and affect leaf growth and morphology of root and shoot (Ahmed et al. 2020). Temperature and moisture stress affects the plants by changes in abscisic acid, salicylic acid, jasmonic acid, and adversely affect the plant resistance to stresses (Asselbergh et al. 2008). It may also reduce the plant's ability to produce growth and defense substances, making the plant susceptible to pathogens.

Increased CO_2 affect photosynthesis and change the structure of plants as well as affect the functioning of ecosystems. Under increased CO_2 conditions, plant organ size also increases, such as leaves and branches (Pritchard et al. 1999), and water use efficiency of plants also increases (Ahmed and Ahmad 2019; Wong et al. 2002). It results in the humid climate, and plant pathogen infection rate may rise. Similarly, elevated ozone can increase the attack of necrotrophic fungi (Sandermann 2000) because leaf composition and structure are affected by the ozone (Karnosky et al. 2002).

12.5 Climate Change Impacts on Host Resistance

The assessment of plant resistance in the context of climate change is complicated. Under drought conditions, infection rate and success tend to decrease (Huber and Gillespie 1992). Fewer symptoms were observed under drought conditions when alfalfa plants were exposed to *verticillium albo-atrum* (Pennypacker et al. 1991). However, in some cases, plant resistance is reduced under drought stress (Christiansen 1982). Resistance genes are also affected by temperature, but it is complicated to assess the effect of temperature on resistance genes and pathogen aggressiveness. Effects of temperature on wheat and barley were studied, and the response of resistance was different to different ranges of temperature (Browder and Eversmeyer 1986; Newton and Young 1996). A higher level of ozone and CO_2 also affects the host resistance (Plazek et al. 2001; Plessl et al. 2005). Reduction in host resistance was observed under elevated CO_2 (Chakraborty and Datta 2003). An increase or decrease in the conduciveness of the disease environment due to climate change can cause shifts in the presence and diversity of resistance genes (Fig. 12.1).

12.6 Climate Change Impacts on Microbial Interaction

Climate change is impacting the microbial communities in the soil and causing various shifts in different interactions. Temperature, CO_2, nitrogen, etc. are the main factors influencing interactions in soils. Increased CO_2 results in a reduction of soil nitrates in grasslands (Barnard et al. 2005) and enhances the nitrogen uptake of plants because of increased growth in plants (Hu et al. 2001). In tallgrass prairies, increased temperature favors plant growth that facilitates fungi dominance in the community and uptake of nitrogen. Lesser availability of nitrogen is experienced by microbial communities, while the type of soil and composition of plants have effects on these observed responses (Hungate et al. 1996). In both agricultural and natural ecosystems prediction of climate change impacts on the disease; suppression is complicated due to variations in the interaction between the microbial species (Davelos et al. 2004). Recent advancements in technology like metagenomic analysis will enhance knowledge about the dynamics of microbes in soil and various environments (Riesenfeld et al. 2004).

Host response to climate change may be affected by symbiosis, as fungal endophytes had shown tolerance to heat, nutrient availability, and water stress (Kannadan and Rudgers 2008; Rodriguez et al. 2008). Brosi et al. (2011) studied the effects of climate change on endophytes, and results concluded that higher infection rates in tall fescue are led by elevated CO_2 levels than the precipitation and temperature.

12.7 Simulation Modeling for Disease Prediction

There are several approaches that can be used in modeling the impacts of climate variability on pathogens and diseases. Different empirical or regressions models can be used to predict the pathogens' success and development of epidemics (Booth et al. 2000). Models can be used for predicting the success of the pathogen in changing environments in the context of a reference climate where pathogens are successful. Climate variability occurs gradually that causes difficulty in studying its effects directly, and hence simulation models can become helpful in outcomes prediction over broader range scenarios. However, problems have been identified in models application for disease forecasting in climate change scenarios (Scherm 2004; Seherm and Coakley 2003). Major issues involve difficulty in acquiring data regarding climate and epidemiological responses (Otten et al. 2004), disease geographic distribution that may lead to higher uncertainties (Katz 2002; Scherm 2000), and ignorance of adaptation potential of plants in simulation models.

12.7.1 History of Disease Modeling

Since the 1960s, models for disease prediction are available, and the first mathematical model was published by Van der Plank (Van der Plank 2013). At the start, the models were empirical. Later on, mechanistic and analytical models were developed. The early model's focus was only based on the units of pathogen and diseased tissue, while the growth of plants was neglected. With the passage of time models for disease prediction became more sophisticated as they included host, environment, and management effects as well. GIS-based models may also be used for disease predictions (Aurambout et al. 2009). At present, a wide range of simple and complex models is in practice for the forecasting and management of disease (Pavan et al. 2011; Rakotonindraina et al. 2012).

Climate change affects the various stages of crops and pathogens, both directly and indirectly. Pathosystems are generally affected by the response of organisms to climate change. However, it is not well understood whether the effects are either positive or negative. To predict the plant diseases in response to climate change, various models had been used in the past (Table 12.1).

12.7.2 Recent Goals and Challenges in Disease Modeling

Integration of crop disease modeling in decision support systems development is mainly dominated by short-term strategic planning to support the scheduling of pesticide application, pest scouting activities, adaptation, and mitigation measures to prevent the diseases (Isard et al. 2015; Magarey et al. 2002). Disease modeling activities are frequently based on the development of relationships using multi-seasonal crop and environmental variables in a specific pest-crop system (Madden et al. 2007). The development of effective decision support systems involves the knowledge of key aspects and dynamics of a system based on the reliable multiple seasonal and specific crop-pest environment data (Madden et al. 2007). Representation of biotic stress and host interaction has been simplified by focusing on the specific environment and pathogens in a system. Moreover, the controlled experiment data can be used to parameterize the model to identify the responses of targeted host and pathogen under a variety of environmental changes. Infection models and Susceptible-Exposed-Infectious-removed (SEIR) models are well-known examples of such disease models (Magarey et al. 2005; Zadoks 1971). For instance, such

Table 12.1 Models used in different regions of the world to study various crop diseases

Region	Crop	Predicted diseases/Pests	References
Australia	Wheat	Yellow dwarf virus	Nancarrow et al. (2014)
Australia	Wheat	Fusarium crown rot	Vary et al. (2015)
Europe	Wheat	Karnal bunt	Baker et al. (2000)
Europe	Rice	Fungal diseases	Bregaglio et al. (2013)
Brazil	Corn	Rust	Moraes et al. (2011)
Denmark	Barley	Powdery mildew	Mikkelsen et al. (2015)
France	Barley	Net blotch	Launay et al. (2014)
United Kingdom	Oilseed rape	Phoma stem canker	Barnes et al. (2010)
Brazil	Soybean	Rust	Alves et al. (2011)
Europe	Sugar beet	Soil borne pathogens	Manici et al. (2014)
Germany	Sugar beet	Leaf spot	Richerzhagen et al. (2011)
Australia	Pea	Ascochyta blight	Salam et al. (2011)
Globally	Potato	Late blight	Sparks et al. (2014)
Brazil	Cocoa	Moniliasis	Moraes et al. (2012b)
Brazil	Coffee	Rust	Ghini et al. (2011)
Brazil	Coffee	Leaf miner	Hamada et al. (2006)
Brazil	Coffee	Nematodes and leaf miner	Ghini et al. (2008)
Brazil	Coffee	Leaf spot	Moraes et al. (2012a)
Globally	Date palm	Fusarium wilt	Shabani and Kumar (2013)
Northern Italy	Grapevines	Powdery mildew	Caffarra et al. (2012)
Italy	Grapevines	Downy mildew	Francesca et al. (2006)
Globally	Grapevines	Downy mildew	Salinari et al. (2007)
France	Grapevines	Botrytis	Gouache et al. (2011)
Brazil	Banana	Black sigtoka	Ghini et al. (2007)
Globally	Banana	Black sigtoka	Junior et al. (2008)
Switzerland	Apple	Fire blight	Hirschi et al. (2012)

disease prediction models can be used to predict the host alterations, disease severity, and yield losses in changing climate (Dillehay et al. 2005).

Priorities for disease modeling are rerouting due to the newly arising challenges and more specific goals. The major challenge for disease modeling is climate change, as it is resulting in the variable average temperature, more erratic rainfall, and humidity. These climate irregularities indicate that previously observed datasets are losing their importance in reliable disease prediction modeling. Moreover, due to these variabilities, several pathogens that were previously unharmful are now becoming detrimental for crops (Gramaje et al. 2016; Berger et al. 2007). Presently, there are increasing concerns about the goal to estimate and predict global food security risks. But it requires the addition of production systems and geographical areas to develop the baseline data for local and robust empirical relationships. However, climate variability makes this goal impossible to achieve due to the nonlinearity of the process involved in statistical models (Garrett et al. 2006). Similarly, climate change impacts the goal of seeking effective estimation and prediction of disease dynamics in future scenarios and impedes the trend analysis based on the several observed weather patterns. To address these challenges, the most efficient and appealing way involves the use of process-based modeling with efficiently designed scenarios and shared modeling approaches among the scientist related to a variety of field. Additionally, the utilization of disease modeling increased its important manifolds, ranging from the strategic decisions making (Duveiller et al. 2007), risk analysis (Venette et al. 2010), research priority and policy making (Willocquet et al. 2004), and resource allocation (Beddow et al. 2015). A new generation of technologically advanced tools is needed to understand the system processes and their dynamics to allow system analysis.

12.7.3 Modeling Approaches in Disease Modeling

Crop growth, performance, and disease dynamics are linked with discrete sets of developmental processes. Efficient understanding and knowledge of these processes can be mobilized to address the problems related to crop pests and diseases. Recently, the concept of integrating pest and disease models with crop models has made easier and effective to study pest and disease dynamics. However, complex disease and crop models are hard to link with each other.

12.7.3.1 Existing Trends in Disease Modeling

Several recent advances have been documented in the domain of designing and integrating the generic disease simulation models to predict the reliable disease and pest damage to crops (Esker et al. 2012; Savary et al. 2006). Process-based disease modeling has emerged as a key approach to quantitatively understand the behavior and address the problems related to the complex crop-pest systems. A typical process-based disease modeling encompasses four basic steps: (1) Infection chain in a disease cycle is considered as the prime focus for analysis (Kranz 1974). (2) Then the functional traits of a pathogen corresponding to infection chain are studied (Pariaud et al. 2009). (3) The efficiency and performance of these traits based on the environment are studied in a pathosystem, as these functional traits are involved in quantitative processes (Zadoks and Schein 1979). (4) Finally, the observed and measured information from these processes is used for the development of process-based models (Savary and Willocquet 2014; Bregaglio and Donatelli 2015). There is a number of disease modeling structures that have been developed with an emphasis on inoculum mobility, spread, efficiency, and production (Rossi et al. 2009). Moreover, a wider range of concepts and development of mechanistic simulation models made it possible to study the interaction between crops, pests, and diseases within a given pathosystem.

The development of generic simulators enables the illustration of several species in a pathosystem. The application of these generic simulators can be extended by adding several specialized biological mechanisms of species. Generic simulators make the disease modeling approach simpler due to the possibility of developing the species-specific disease model. Moreover, these simulators provide a framework to collect adequate data for disease modeling regarding insect phenology, physiology (Welch et al. 1978), populations (Yonow et al. 2004), development, and reproduction (Hong et al. 2015; Sutherst et al. 2007).

Knowledge sharing and modification among the wider scientific communities can enhance the impacts and progress of disease modeling (Stein et al. 2002; Tatusov et al. 2000). For instance, AgMIP (Agricultural Model Inter-comparison and Improvement Project) is a recent knowledge sharing example of international collaboration to assess the impacts of climate change on global agriculture based on global agricultural modeling (Rosenzweig et al. 2013). These approaches can mobilize the generic disease modeling platform by combining all fragmented theories and concepts existing in disease modeling globally. APSnet (American Phytopathology Society) plant health instructor is a well-known illustration of such approaches (Bregaglio and Donatelli 2015; Savary and Willocquet 2014). Simulated disease epidemics can be used as input in crop models accounting for the physiological impacts of disease on crops and damage mechanisms (Rouse 1988). Over the past few decades, crop growth models involving damage mechanisms have been developed with the concept of integration of disease and crop models to simulate the crop yield losses due to disease epidemics (Boote et al. 1983; Bastiaans et al. 1994).

12.7.3.2 Data Requirements for Disease Modeling

Most common data inputs for disease modeling are based on variables such as temperature, precipitation, relative humidity, and leaf wetness with hourly or daily resolutions (Magarey et al. 2001). However, the soil variables and wind are considered in more complex models focusing on soil pathogens. Mostly the daily data is sufficient for disease models, but some models need hourly data to improve the accuracy and reliability of disease simulations and scenarios development (Bregaglio et al. 2010). However, the gridded current and forecasted data with fine resolution can be obtained by numerical weather models such as AGRI4CAST in Europe, RTMA (Real Time Mesoscale Analysis System) in the United States (De Pondeca et al. 2011), and CFSR (Climate Forecast System Reanalysis) globally (Saha et al. 2014). Data regarding leaf wetness is a limitation due to the unavailability of such data, but simulations models are now being used as alternatives to target the climate change scenarios (Magarey et al. 2006; Bregaglio et al. 2012).

12.7.3.3 Calibration and Evaluation of Disease Models

Models calibration is the fine-tuning of models with real-time data to improve the model accuracy and application in a desired environment or pathosystem. Most of the disease and pest models are calibrated with experimental data obtained from controlled conditions. Data regarding variables such as pest virulence, development, fecundity, longevity, mortality, and environment of pathosystem is needed to parameterize and calibrate the models (Régnière et al. 2012). Similarly, data from the experiments with controlled temperature and leaf wetness can be used to calibrate the infection models (Magarey et al. 2005; Madden and Ellis 1988). Moreover, when the data is unavailable to calibrate the model, then closely related species can be used to identify parameter, and then field studies are enabled to see if the estimated parameters are in line with observed data or not.

Model evaluation is necessary to estimate the accuracy of simulations in comparison with real-time data. Several ways and methods can be used to evaluate the pest and disease models (Rabbinge 1993). The most common approach to evaluate the models involves the comparison of observed and simulated data in terms of disease severity, incidence, and damage. However, evaluation of disease models is usually done by the developing party or by the end-user according to their pathosystems. Overfitting is a serious concern in the model evaluation and to perform simulation in different pathosystems. Overfitting occurs when the output of model adjusted parameters closely matches the data used for calibration but leads to compromised accuracy when simulations are performed over an independent dataset.

12.7.4 Frameworks for Disease Modeling

In the past various types of models were being used by scientists to model plant pathogens and disease. Matrix models have been used widely over several decades in the past for determining the population densities of pests and insects in a certain region (Lewis 1977). Several equations were used in competitive models to determine the effects of competition between crops and pathogen species (Kaplan and Denno 2007).

12.7.5 Recent Development and Addition in Modeling Frameworks

Recently, disease modeling gained importance and various developments occurred. Different modeling frameworks are developed for pests and disease modeling in the last few years.

12.7.5.1 APSnet

It is an (American Phytopathology Society) website that provides a module to help in modeling epidemiology and crop loss analysis. It has various models such as GENEPEST for simulations (Donatelli et al. 2017) and provides guidance for running the simulation models. Savary et al. (2006) summarized an overall disease modeling framework to simulate the disease impacts on agriculture systems using such models. The development of this platform involved several steps. Multilocational farmer's field survey was conducted for several years to observe the production systems and associated injuries. Similarly, the field experiments performed to assess disease damage and crop losses. Mechanistic models were developed by using this collected data based on the damage mechanisms. This approach was used to simulate pest and disease systems in Asian rice-growing regions (Willocquet et al. 2004; Willocquet et al. 2002) and European and UK wheat-growing regions (Willocquet et al. 2008; Foster et al. 2004).

12.7.5.2 APSIM-DYMEX

APSIM (Agriculture Production Systems Simulator) is a modeling framework developed over the last two decades (Holzworth et al. 2015). APSIM does not have the ability to consider pests and diseases. But recently, it has been linked with DYMEX (Whish et al. 2015). DYMEX is a mechanistic model for simulation of pests, diseases, and weeds life cycles. Models involved in DYMEX are enabled to run in the DYMAX simulator (Whish et al. 2015). The coupling of these modules enabled the multi-point APSIM features with simplified communication within both models. Both these frameworks can simultaneously model the crop growth and disease dynamics.

12.7.5.3 BioMA-Diseases

For fungal plant disease modeling, this framework was developed, having four extendable software (Bregaglio and Donatelli 2015). This framework is used for modeling the impacts of fungal epidemics on plant growth. It simulates and quantifies the polycyclic fungal epidemics and impacts of epidemics on crops. BioMA is a public-domain framework to parameterize and run the biophysical models in the agriculture field (Fig.12.2). This module was applied to study major diseases such as brown rust (wheat) and leaf blast (Carlsson et al. 2008) in Europe, China, and Italy and assess the model behavior under diverse environments (Bregaglio et al. 2016).

12.7.5.4 NAPPFAST

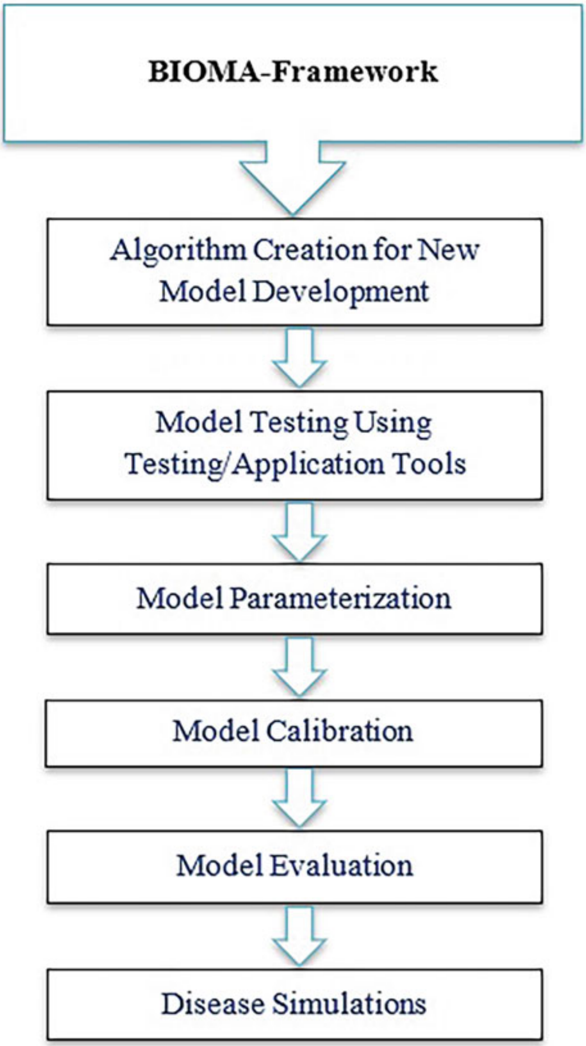
NAPPFAST (North Carolina State University/Animal and Plant Health Inspection Service Plant Pest Forecasting System) module was developed during a project from 2002 to 2013 (Magarey et al. 2007; Magarey et al. 2015) with having an Internet-based GUI (graphical user interface). This module was interlinked with the weather datasets. It has three simulation modeling templates: phenology models (with degree-day approach), infection models (with pathogens and diseases approach), and generic models (with a simple empirical model approach). All these templates were generic to meet the diverse needs of users. NAPPFAST has the ability of pest risk mapping with several resolutions (Magarey et al. 2011).

12.7.6 Case Study

Climate variability has significant impact on interactions among plants, pests, and diseases. However, limited research has been conducted on disease severity, incidence, and distribution in response to the changing climate. Few studies simulated the future potential changes in disease epidemics and plant health (Sparks et al. 2014; Bregaglio et al. 2013). Application of disease models can dissect the role of climate change in disease spread, severity, and plant health.

Black Sigatoka is a major disease of tropical crops especially banana. The causal agent of this disease *Pseudocercospora fijiensis* is dependent on microclimate and weather variables. It requires the high relative humidity and leaf wet surface to

Fig. 12.2 BIOMA modeling framework



germinate and cause infections in banana plant (Uchôa et al. 2012). A disease model for simulating the Black Sigatoka in future climate change scenarios was developed by using the climate data of banana growing areas in Caribbean and Latin America (Bebber 2019). During the process of model development past 60 years observed and reported climate data was used to parameterize the model. The temperature (T_{min}, T_{max}, and T_{opt}) and leaf wetness data were used to develop and parameterize the model. The data regarding these variables was observed at 3-h intervals in studied regions.

The model simulated the fraction of spore's cohort development F (t) over the time (t) during the wet intervals and had a Weibull hazard (H) function based on prevailing temperature (T). The temperature-dependent cohort development rate (r) was simulated on the basis of cardinal temperatures such as $T_{\min}$, $T_{\max}$, and T_{opt}. Model was parameterized using observations and simulations based on $T_{\min}$, $T_{\max}$, T_{opt}, the scale factor (α) and shape parameter (ɤ) for hazard function.

$$F\ (t, T) = 1 - \bar{e}^{H(t,T)}$$

$$H\ (t, T) = r(T)\ [t/\alpha]^{\gamma}$$

$$r(T) = \left[T_{\max} - T/T_{\max} - T_{\mathrm{opt}}\right] * \left[T - T_{\min}/T_{\mathrm{opt}} - T_{\min}\right]^{T_{\mathrm{opt}} - T_{\min}/T_{\max} - T_{\mathrm{opt}}}$$

Disease simulations using this model defined the Black Sigatoka infection risks on the basis of total number of simulated spore's cohorts per hour over a specific time duration. Disease simulations predicted the 44% increase in infection rate of Black Sigatoka across Caribbean and Latin America since 1960. This simulated increase was due to the increased temperature and leaf surface wetness that favored the pathogen infection ability. Conclusively, the changing climate and global trading of banana resulted in the establishment of more conducive environment in banana growing regions for Black Sigatoka infection.

12.7.7 Strategies for Effective Disease Modeling

There are some effective strategies that can be used to enhance the reliability of simulation in agricultural disease and crop modeling. These strategies comprise the actions to enhance the availability of quality data for disease model input and model evaluation, coupling with crop models, and develop the modeler's community to share the knowledge.

Process-based disease modeling is aimed to reproduce the dynamics of biophysical processes depending on the input variables. Pathogen growth and development are highly dependent on weather variables; hence the model should modulate the responses according to the fluctuations in model input variables (Pfender et al. 2012; Magarey et al. 2005). Therefore, the availability of high resolution and quality data is essential to calibrate the model, especially for the moisture- and temperature-mediated responses. Low-quality data reduces the reliability of model empirical coefficients and impede the model fitness and application. Hence, the quality input dataset is a key in crop disease modeling and the high-resolution real-time data regarding temperature, humidity, and leaf wetness are required to minimize the uncertainties during model calibration and evaluation.

Field measurements and data about the impacts of diseases on crops have been collected in previous years, but these observation methods had no standards and usually are not coupled with crop and weather data to be used as disease modeling data input (Esker et al. 2012; Nutter Jr 1989). Consequently, the disease model validation was limited across diversified environments (Willocquet et al. 2004; Willocquet et al. 2002). Hence, the development of designs, guides, templates, and protocols is needed to collect the adequate and required standard data to validate the disease models effectively (Willocquet et al. 2000). Detailed observations should include the disease or pest data (Disease severity, incidence, injury level), weather data (temperature, humidity, and leaf wetness), and crop data (physiological processes such as respiration, photosynthesis, senescence, etc.) (Esker et al. 2012; Savary et al. 2006).

The disease and host crop dynamics are the coupling points among disease and crop models. Quantification of disease damage and injuries can be assessed by performing experiments in different pathosystems (Robert et al. 2005; Bassanezi et al. 2001). Mathematical representation of these injuries may enable the integration into crop models for simulation of biophysical processes (Pavan and Fernandes 2009). Disease simulation modeling can be done in conjunction with crop growth models to assess the impacts of disease on crop growth. However, the integration of disease and crop models may lead to issues such as complexity in model structures, binary incompatibilities, and sharing difficulties. There are some critical points to be considered for integrating the disease and crop models. Identification and adequate knowledge about damage mechanisms are necessary to simulate the disease impacted outputs by crop models. The disease model's output must be compatible directly or indirectly with the crop model variables. Moreover, the communication compatibilities of both types of models must also be considered for the efficient integration of disease and crop models. Crop model selection to integrate with the disease model must consider the presence of variables affected by the disease in both kinds of models.

Lack of modeling community and cohesive research hampered the development of improved and advanced disease models. Such modelers community development efforts may help in the efficient understanding of biophysical processes, system behaviors, and bridge the communication gaps. However, there are several limitations in such efforts like limited availability of generic disease model frameworks that allow the shift between pathogens and pests. Similarly, modeling cooperation efforts are limited due to the inadequate availability of standard data. In 2015, PeDiMiP (Pest and Disease Modeling Inter-comparison Project) was launched as part of the AgMIP (Agricultural Modeling Inter-comparison Project) to improve disease and pest modeling and to assess the impacts of climate change on crop losses. This project is mainly focused on modeling of crop health, wheat rust, and potato late blight diseases.

12.8 Plant Disease Management

Climate change increases the plant protection complexity. It also causes changes in the chemical market due to the changes in pathogen distribution. Similarly, climate change results in the resistance development in pathogens which ultimately leads to the increased cost for crop production due to high application rates and treatments (Juroszek and Von Tiedemann 2011). Some production systems show more flexibility than others to adopt better practices and strategies to reduce certain diseases.

However, adaptation strategies depend on cost-benefit analyses. One of the great strategies in changing climate involves the efficiency evaluation of current biological, physical, and chemical practices. We can prevent the increased risk of diseases under predicted climate change by using various agronomic practices (irrigation, crop rotation, etc.) that can minimize the overwintering amount of inoculum (Juroszek and Von Tiedemann 2011). There is a need for adjustment in management strategies under changing climate. In biological control, the populations vary with changes in environmental conditions. Under the extreme condition of the environment, the populations of biological agents may become smaller and do not recover even in favorable conditions. Disease management may be affected by climate change and results in uncertainties in decision making when climate variability is greater. But, El Nino-based climate predictions were useful in decision making for farmers of Zimbabwe (Patt et al. 2005).

12.9 Knowledge Gaps and Future Directions

Over the past decade, climate change studies have improved the understanding of how environmental factors impact plant disease epidemics. Climate change is not occurring in isolation, and it may intensify in the coming years. While only a few studies were carried out to evaluate the combined impact of multiple factors, evaluation of the combined effect of various factors on hosts, pathogens, and diseases is needed. Simulation modeling provides an opportunity to simulate several factors simultaneously. While climatic models used to study the impacts of climate change on plant diseases focused on a few variables like precipitation and rainfall, models based on multiple factors should be used to study climate changes and plant disease relationships. Molecular analysis and mechanistic studies can help to consider the change in plant diseases as a result of climate change. Over the past few years, foliar diseases are mainly focused while little work has been done on soilborne diseases. Therefore, studies should be conducted to evaluate the climate change impacts on soilborne diseases.

Plant disease management and severity will probably be increased due to climate change. Prediction of diseases and their management is of great interest to farmers and agro-industries. The following plant protection strategies can help in disease management to a certain extent:

1. Use of models to forecast disease epidemics
2. Crop rotation
3. Diversity in crop species
4. Use cultivars with superior disease resistance
5. Adjustment in sowing time
6. Effective quarantine measures
7. Use of Integrated Pest Management strategy

12.10 Conclusion

Climate change is impacting the crops, trees, and agricultural productivity and, at the same time, influencing the pathogens and disease development in plants. It is a major challenge to understand and realize the impacts of climate change in terms of plant diseases, pathogens, and health of plants because of the limitation in the knowledge that how various changes in the atmosphere are affecting the physiology of host and pathogens development, spread and resistance in host and pathogen. Achievements in plant protection are limited due to the lack of knowledge about changes in the environment, pathogen, and host interaction globally. For effective plant protection and disease management, detailed study and research are needed to understand the relationship among the changing environment, pathogens, and hosts under the climate change scenario. Modeling of diseases can become more effective if we combine the developed tools in our studies.

References

Ahmad S, Hasanuzzaman M (2020) Cotton production and uses. Springer Nature Singapore Pvt. Ltd., Singapore, 641 pp. https://doi.org/10.1007/978-981-15-1472-2

Ahmed M (2020) Introduction to modern climate change. Andrew E. Dessler: Cambridge University Press, 2011, 252 pp, ISBN-10: 0521173159. Sci Total Environ 734:139397. https://doi.org/10.1016/j.scitotenv.2020.139397

Ahmed M, Ahmad S (2019) Carbon dioxide enrichment and crop productivity. In: Hasanuzzaman M (ed) Agronomic crops, Management practices, vol 2. Springer Singapore, Singapore, pp 31–46. https://doi.org/10.1007/978-981-32-9783-8_3

Ahmed M, Stockle CO (2016) Quantification of climate variability, adaptation and mitigation for agricultural sustainability. Springer Nature Singapore Pvt. Ltd., Singapore, 437 pp. https://doi.org/10.1007/978-3-319-32059-5

Ahmed K, Shabbir G, Ahmed M, Shah KN (2020) Phenotyping for drought resistance in bread wheat using physiological and biochemical traits. Sci Total Environ 729:139082. https://doi.org/10.1016/j.scitotenv.2020.139082

Alves MC, de Carvalho L, Pozza E, Sanches L, Maia JS (2011) Ecological zoning of soybean rust, coffee rust and banana black sigatoka based on Brazilian climate changes. Procedia Environ Sci 6:35–49

Asselbergh B, De Vleesschauwer D, Hofte M (2008) Global switches and fine-tuning—ABA modulates plant pathogen defense. Mol Plant-Microbe Interact 21(6):709–719

Aurambout J, Finlay KJ, Luck J, Beattie G (2009) A concept model to estimate the potential distribution of the Asiatic citrus psyllid (Diaphorina citri Kuwayama) in Australia under climate change—a means for assessing biosecurity risk. Ecol Model 220(19):2512–2524

Baker R, Sansford C, Jarvis C, Cannon R, MacLeod A, Walters K (2000) The role of climatic mapping in predicting the potential geographical distribution of non-indigenous pests under current and future climates. Agric Ecosyst Environ 82(1–3):57–71

Barnard R, Leadley PW, Lensi R, Barthes L (2005) Plant, soil microbial and soil inorganic nitrogen responses to elevated CO2: a study in microcosms of Holcus lanatus. Acta Oecol 27(3):171–178

Barnes AP, Wreford A, Butterworth MH, Semenov MA, Moran D, Evans N, Fitt BD (2010) Adaptation to increasing severity of phoma stem canker on winter oilseed rape in the UK under climate change. J Agric Sci 148(6):683–694

Bassanezi R, Amorim L, Filho AB, Hau B, Berger R (2001) Accounting for photosynthetic efficiency of bean leaves with rust, angular leaf spot and anthracnose to assess crop damage. Plant Pathol 50(4):443–452

Bastiaans L, Rabbinge R, Zadoks J (1994) Understanding and modeling leaf blast effects on crop physiology and yield. In: Rice blast disease. IRRI, Los Baños, pp 357–380

Bebber DP (2019) Climate change effects on black Sigatoka disease of banana. Philos Trans R Soc B 374(1775):20180269

Beddow JM, Pardey PG, Chai Y, Hurley TM, Kriticos DJ, Braun H-J, Park RF, Cuddy WS, Yonow T (2015) Research investment implications of shifts in the global geography of wheat stripe rust. Nat Plants 1(10):15132

Berger S, Sinha AK, Roitsch T (2007) Plant physiology meets phytopathology: plant primary metabolism and plant–pathogen interactions. J Exp Bot 58(15–16):4019–4026

Boote K, Jones J, Mishoe J, Berger R (1983) Coupling pests to crop growth simulators to predict yield reductions [Mathematical models]. Phytopathology (USA) 73:1581

Booth T, Jovanovic T, Old K, Dudzinski M (2000) Climatic mapping to identify high-risk areas for Cylindrocladium quinqueseptatum leaf blight on eucalypts in mainland South East Asia and around the world. Environ Pollut 108(3):365–372

Bosch J, Carrascal LM, Duran L, Walker S, Fisher MC (2007) Climate change and outbreaks of amphibian chytridiomycosis in a montane area of Central Spain; is there a link? Proc R Soc Lond B Biol Sci 274(1607):253–260

Bradley BA, Blumenthal DM, Early R, Grosholz ED, Lawler JJ, Miller LP, Sorte CJ, D'Antonio CM, Diez JM, Dukes JS (2012) Global change, global trade, and the next wave of plant invasions. Front Ecol Environ 10(1):20–28

Brasier CM (1996) Phytophthora cinnamomi and oak decline in southern Europe. Environmental constraints including climate change. In: Annales des Sciences Forestieres. EDP Sciences (Édition Diffusion Presse Sciences), Ray Ulysse, vol 2–3, pp 347–358

Brasier CM, Scott JK (1994) European oak declines and global warming: a theoretical assessment with special reference to the activity of Phytophthora cinnamomi. EPPO Bull 24(1):221–232

Bregaglio S, Donatelli M (2015) A set of software components for the simulation of plant airborne diseases. Environ Model Softw 72:426–444

Bregaglio S, Donatelli M, Confalonieri R, Acutis M, Orlandini S (2010) An integrated evaluation of thirteen modelling solutions for the generation of hourly values of air relative humidity. Theor Appl Climatol 102(3–4):429–438

Bregaglio S, Cappelli G, Donatelli M (2012) Evaluating the suitability of a generic fungal infection model for pest risk assessment studies. Ecol Model 247:58–63

Bregaglio S, Donatelli M, Confalonieri R (2013) Fungal infections of rice, wheat, and grape in Europe in 2030–2050. Agron Sustain Dev 33(4):767–776

Bregaglio S, Titone P, Cappelli G, Tamborini L, Mongiano G, Confalonieri R (2016) Coupling a generic disease model to the WARM rice simulator to assess leaf and panicle blast impacts in a temperate climate. Eur J Agron 76:107–117

Brosi GB, McCulley RL, Bush LP, Nelson JA, Classen AT, Norby RJ (2011) Effects of multiple climate change factors on the tall fescue–fungal endophyte symbiosis: infection frequency and tissue chemistry. New Phytol 189(3):797–805

Browder L, Eversmeyer M (1986) Interactions of temperature and time with some Puccinia recondita: triticum corresponding gene pairs. Phytopathology (USA) 76:1286

Caffarra A, Rinaldi M, Eccel E, Rossi V, Pertot I (2012) Modelling the impact of climate change on the interaction between grapevine and its pests and pathogens: european grapevine moth and powdery mildew. Agric Ecosyst Environ 148:89–101

Carlsson AS, Chanana NP, Gudu S, Suh MC, Were BAI (2008) Sesame. compendium of transgenic crop plants

Carter TR, Saarikko RA, Niemi KJ (1996) Assessing the risks and uncertainties of regional crop potential under a changing climate in Finland. Agric Food Sci 5(3):329–350

Chakraborty S (2005) Potential impact of climate change on plant-pathogen interactions. Australas Plant Pathol 34(4):443–448
Chakraborty S (2013) Migrate or evolve: options for plant pathogens under climate change. Glob Chang Biol 19(7):1985–2000
Chakraborty S, Datta S (2003) How will plant pathogens adapt to host plant resistance at elevated CO2 under a changing climate? New Phytol 159(3):733–742
Chakraborty S, Murray G, White N (2002) Impact of climate change on important plant diseases in Australia: a report for the Rural Industries Research and Development Corporation
Christiansen MN (1982) Breeding plants for less favorable environments
Coakley SM, Scherm H, Chakraborty S (1999) Climate change and plant disease management. Annu Rev Phytopathol 37(1):399–426
Davelos AL, Kinkel LL, Samac DA (2004) Spatial variation in frequency and intensity of antibiotic interactions among Streptomycetes from prairie soil. Appl Environ Microbiol 70(2):1051–1058
De Pondeca MS, Manikin GS, DiMego G, Benjamin SG, Parrish DF, Purser RJ, Wu W-S, Horel JD, Myrick DT, Lin Y (2011) The real-time mesoscale analysis at NOAA's National Centers for Environmental Prediction: current status and development. Weather Forecast 26(5):593–612
Desprez-Loustau M-L, Marcais B, Nageleisen L-M, Piou D, Vannini A (2006) Interactive effects of drought and pathogens in forest trees. Ann For Sci 63(6):597–612
Dillehay B, Calvin DD, Roth GW, Hyde J, Kuldau GA, Kratochvil R, Russo J, Voight D (2005) Verification of a European corn borer (Lepidoptera: Crambidae) loss equation in the major corn production region of the northeastern United States. J Econ Entomol 98(1):103–112
Donatelli M, Magarey RD, Bregaglio S, Willocquet L, Whish JP, Savary S (2017) Modelling the impacts of pests and diseases on agricultural systems. Agric Syst 155:213–224
Duveiller E, Singh RP, Nicol JM (2007) The challenges of maintaining wheat productivity: pests, diseases, and potential epidemics. Euphytica 157(3):417–430
Esker PD, Savary S, McRoberts N (2012) Crop loss analysis and global food supply: focusing now on required harvests. CAB Rev 7(052):1–14
Foster GN, Blake S, Tones SJ, Barker I, Harrington R (2004) Occurrence of barley yellow dwarf virus in autumn-sown cereal crops in the United Kingdom in relation to field characteristics. Pest Manag Sci Formerly Pestic Sci 60(2):113–125
Francesca S, Simona G, Francesco Nicola T, Andrea R, Vittorio R, Federico S, Cynthia R, Maria Lodovica G (2006) Downy mildew (Plasmopara viticola) epidemics on grapevine under climate change. Glob Chang Biol 12(7):1299–1307
Frankel S (2007) Climate change's influence on sudden oak death, PACLIM 2007, Monterey, CA, 13–15 May 2007
Fuhrer J (2003) Agroecosystem responses to combinations of elevated CO2, ozone, and global climate change. Agric Ecosyst Environ 97(1–3):1–20
Garbelotto M, Linzer R, Nicolotti G, Gonthier P (2010) Comparing the influences of ecological and evolutionary factors on the successful invasion of a fungal forest pathogen. Biol Invasions 12 (4):943–957
Garrett KA, Dendy SP, Frank EE, Rouse MN, Travers SE (2006) Climate change effects on plant disease: genomes to ecosystems. Annu Rev Phytopathol 44:489–509
Garrett KA, Nita M, De Wolf E, Esker PD, Gomez-Montano L, Sparks AH (2015) Plant pathogens as indicators of climate change. In: Climate change, Second edn. Elsevier, Dordrecht, pp 325–338
Ghini R, Hamada E, Goncalves RR, Gasparotto L, Pereira JCR (2007) Risk analysis of climatic change on black Sigatoka on banana in Brazil. Fitopatol Bras 32(3):197–204
Ghini R, Hamada E, Júnior P, José M, Marengo JA, Gonçalves RRDV (2008) Risk analysis of climate change on coffee nematodes and leaf miner in Brazil. Pesq Agrop Brasileira 43 (2):187–194
Ghini R, Hamada E, Junior P, Jose M, Goncalves RRDV (2011) Incubation period of Hemileia vastatrix in coffee plants in Brazil simulated under climate change. Summa Phytopathol 37 (2):85–93

Gioria R, Brunelli K, Kobori R (2008) Impacto potencial das mudanças climáticas sobre as doenças de hortaliças: tomate, um estudo de caso. Summa Phytopathologica 34(supl):187–194

Gouache D, Roche R, Pieri P, Bancal M-O (2011) Evolution of some pathosystems on wheat and vines. Climate change, agriculture and forests in France: simulations of the impacts on the main species The Green Book of the CLIMATOR project (2007–2010), part C (The crops), section B5 Health:113–126

Gramaje D, Baumgartner K, Halleen F, Mostert L, Sosnowski M, Úrbez-Torres J, Armengol J (2016) Fungal trunk diseases: a problem beyond grapevines. Plant Pathol 65(3):355–356

Grulke NE (2011) The nexus of host and pathogen phenology: understanding the disease triangle with climate change. New Phytol 189(1):8–11

Hamada E, Ghini R, GONÇALVES RdV (2006) Efeito da mudança climática sobre problemas fitossanitários de plantas: metodologia de elaboração de mapas. Embrapa Meio Ambiente-Artigo em periódico indexado (ALICE)

Hibberd J, Whitbread R, Farrar J (1996) Effect of 700 μmol mol− $1CO_2$ and infection with powdery mildew on the growth and carbon partitioning of barley. New Phytol 134(2):309–315

Hirschi M, Stoeckli S, Dubrovsky M, Spirig C, Calanca P, Rotach M, Fischer A, Duffy B, Samietz J (2012) Downscaling climate change scenarios for apple pest and disease modeling in Switzerland. Earth Syst Dynam 3(1):33–47

Holzworth DP, Snow V, Janssen S, Athanasiadis IN, Donatelli M, Hoogenboom G, White JW, Thorburn P (2015) Agricultural production systems modelling and software: current status and future prospects. Environ Model Softw 72:276–286

Hong SC, Magarey R, Borchert DM, Vargas RI, Souder S (2015) Site-specific temporal and spatial validation of a generic plant pest forecast system with observations of Bactrocera dorsalis (oriental fruit fly). NeoBiota 27:37

Hu S, Chapin F III, Firestone M, Field C, Chiariello N (2001) Nitrogen limitation of microbial decomposition in a grassland under elevated CO 2. Nature 409(6817):188

Huber L, Gillespie T (1992) Modeling leaf wetness in relation to plant disease epidemiology. Annu Rev Phytopathol 30(1):553–577

Hungate BA, Canadell J, Chapin FS (1996) Plant species mediate changes in soil microbial N in response to elevated CO2. Ecology 77(8):2505–2515

Huseynova I, Sultanova N, Mammadov A, Suleymanov S, Aliyev JA (2014) Biotic stress and crop improvement. In: Improvement of crops in the era of climatic changes. Springer, New York, pp 91–120

Isard SA, Russo JM, Magarey RD, Golod J, VanKirk JR (2015) Integrated pest information platform for extension and education (iPiPE): progress through sharing. J Integr Pest Manag 6 (1):15

Jung T (2009) Beech decline in Central Europe driven by the interaction between Phytophthora infections and climatic extremes. For Pathol 39(2):73–94

Junior J, Valadares Júnior R, Cecílio RA, Moraes WB, FXRD V, Alves FR, Paul PA (2008) Worldwide geographical distribution of Black Sigatoka for banana: predictions based on climate change models. Scientia Agricola 65(SPE):40–53

Juroszek P, Von Tiedemann A (2011) Potential strategies and future requirements for plant disease management under a changing climate. Plant Pathol 60(1):100–112

Juroszek P, von Tiedemann A (2015) Linking plant disease models to climate change scenarios to project future risks of crop diseases: a review. J Plant Dis Prot 122(1):3–15

Kannadan S, Rudgers J (2008) Endophyte symbiosis benefits a rare grass under low water availability. Funct Ecol 22(4):706–713

Kaplan I, Denno RF (2007) Interspecific interactions in phytophagous insects revisited: a quantitative assessment of competition theory. Ecol Lett 10(10):977–994

Karnosky D, Percy KE, Xiang B, Callan B, Noormets A, Mankovska B, Hopkin A, Sober J, Jones W, Dickson R (2002) Interacting elevated CO2 and tropospheric O3 predisposes aspen (Populus tremuloides Michx.) to infection by rust (Melampsora medusae f. sp. tremuloidae). Glob Chang Biol 8(4):329–338

Katz RW (2002) Techniques for estimating uncertainty in climate change scenarios and impact studies. Clim Res 20(2):167–185

Kranz J (1974) The role and scope of mathematical analysis and modeling in epidemiology. In: Epidemics of plant diseases. Springer, Berlin, pp 7–54

Kudela V (2009) Potential impact of climate change on geographic distribution of plant pathogenic bacteria in Central Europe. Plant Prot Sci 45(Special Issue):S27–S32

Ladanyi M, Horvath L (2010) A review of the potential climate change impact on insect populations- general and agricultural aspects. Appl Ecol Environ Res 8(2):143–152

Launay M, Caubel J, Bourgeois G, Huard F, de Cortazar-Atauri IG, Bancal M-O, Brisson N (2014) Climatic indicators for crop infection risk: application to climate change impacts on five major foliar fungal diseases in Northern France. Agric Ecosyst Environ 197:147–158

Legler SE, Caffi T, Rossi V (2012) A nonlinear model for temperature-dependent development of Erysiphe necator chasmothecia on grapevine leaves. Plant Pathol 61(1):96–105

Lewis E (1977) On the generation and growth of a population. In: Mathematical demography. Springer, Berlin, pp 221–225

Luo Y, Tebeest D, Teng P, Fabellar N (1995) Simulation studies on risk analysis of rice leaf blast epidemics associated with global climate change in several Asian countries. J Biogeography 22:673–678

Madden L, Ellis M (1988) How to develop plant disease forecasters. In: Experimental techniques in plant disease epidemiology. Springer, Berlin, pp 191–208

Madden LV, Hughes G, Van Den Bosch F (2007) The study of plant disease epidemics

Magarey R, Seem R, Russo J, Zack J, Waight K, Travis J, Oudemans P (2001) Site-specific weather information without on-site sensors. Plant Dis 85(12):1216–1226

Magarey R, Travis J, Russo J, Seem R, Magarey P (2002) Decision support systems: quenching the thirst. Plant Dis 86(1):4–14

Magarey R, Sutton T, Thayer C (2005) A simple generic infection model for foliar fungal plant pathogens. Phytopathology 95(1):92–100

Magarey R, Russo J, Seem R (2006) Simulation of surface wetness with a water budget and energy balance approach. Agric For Meteorol 139(3–4):373–381

Magarey R, Fowler G, Borchert D, Sutton T, Colunga-Garcia M, Simpson J (2007) NAPPFAST: an internet system for the weather-based mapping of plant pathogens. Plant Dis 91(4):336–345

Magarey RD, Borchert D, Engle J, Colunga-Garcia M, Koch FH, Yemshanov D (2011) Risk maps for targeting exotic plant pest detection programs in the United States. EPPO Bull 41(1):46–56

Magarey RD, Borchert DM, Fowler GA, Hong SC, Venette R (2015) The NCSU/APHIS plant pest forecasting system (NAPPFAST). Pest risk modelling and mapping for invasive alien species. CABI, Wallingford, pp 82–96

Manici L, Bregaglio S, Fumagalli D, Donatelli M (2014) Modelling soil borne fungal pathogens of arable crops under climate change. Int J Biometeorol 58(10):2071–2083

Melloy P, Aitken E, Luck J, Chakraborty S, Obanor F (2014) The influence of increasing temperature and CO2 on Fusarium crown rot susceptibility of wheat genotypes at key growth stages. Eur J Plant Pathol 140(1):19–37

Mikkelsen BL, Jørgensen RB, Lyngkjær MF (2015) Complex interplay of future climate levels of CO 2, ozone and temperature on susceptibility to fungal diseases in barley. Plant Pathol 64 (2):319–327

Moraes WB, Peixoto L, Jesus Junior W, Moraes W, Cecilio R (2011) Impacts of climate change on the risk on occurrence of the southern corn rust of the maize in Brasil. Enciclopedia Biosfera 7:1–12

Moraes BW, de Jesus Junior CW, de Azevedo Peixoto L, Moraes WB, Coser SM, Cecílio RA (2012a) Impact of climate change on the phoma leaf spot of coffee in Brazil. Interciencia 37:272–278

Moraes BW, Júnior J, Peixoto LA, Moraes WB, Furtado EL, LGD S, Cecílio RA, Alves FR (2012b) An analysis of the risk of cocoa moniliasis occurrence in Brazil as the result of climate change. Summa Phytopathol 38(1):30–35

Nancarrow N, Constable FE, Finlay KJ, Freeman AJ, Rodoni BC, Trebicki P, Vassiliadis S, Yen AL, Luck JE (2014) The effect of elevated temperature on barley yellow dwarf virus-PAV in wheat. Virus Res 186:97–103

Newton A, Young I (1996) Temporary partial breakdown of Mlo-resistance in spring barley by the sudden relief of soil water stress. Plant Pathol 45(5):973–977

Nutter FW Jr (1989) Detection and measurement of plant disease gradients in peanut with a multispectral radiometer. Phytopathology 79(9):958–963

Otten W, Bailey DJ, Gilligan CA (2004) Empirical evidence of spatial thresholds to control invasion of fungal parasites and saprotrophs. New Phytol 163(1):125–132

Pariaud B, Ravigné V, Halkett F, Goyeau H, Carlier J, Lannou C (2009) Aggressiveness and its role in the adaptation of plant pathogens. Plant Pathol 58(3):409–424

Patt A, Suarez P, Gwata C (2005) Effects of seasonal climate forecasts and participatory workshops among subsistence farmers in Zimbabwe. Proc Natl Acad Sci 102(35):12623–12628

Pavan W, Fernandes JMC (2009) Uso de orientação a objetos no desenvolvimento de modelos de simulação de doenças de plantas genéricos. Revista Brasileira de Agroinformática 9(1):12–27

Pavan W, Fraisse C, Peres N (2011) Development of a web-based disease forecasting system for strawberries. Comput Electron Agric 75(1):169–175

Pennypacker B, Leath K, Hill R Jr (1991) Impact of drought stress on the expression of resistance to Verticillium albo-atrum in alfalfa. Phytopathology (USA) 81(9):1014

Perkins LB, Leger EA, Nowak RS (2011) Invasion triangle: an organizational framework for species invasion. Ecol Evol 1(4):610–625

Pfender W, Gent D, Mahaffee W (2012) Sensitivity of disease management decision aids to temperature input errors associated with sampling interval and out-of-canopy sensor placement. Plant Dis 96(5):726–736

Plazek A, Hura K, Rapacz M, Zur I (2001) The influence of ozone fumigation on metabolic efficiency and plant resistance to fungal pathogens. J Appl Bot Food Qual 75:8–13

Plessl M, Heller W, Payer HD, Elstner E, Habermeyer J, Heiser I (2005) Growth parameters and resistance against Drechslera teres of spring barley (Hordeum vulgare L. cv. Scarlett) grown at elevated ozone and carbon dioxide concentrations. Plant Biol 7(6):694–705

Pritchard S, Rogers H, Prior SA, Peterson C (1999) Elevated CO2 and plant structure: a review. Glob Chang Biol 5(7):807–837

Prospero S, Grünwald N, Winton L, Hansen E (2009) Migration patterns of the emerging plant pathogen Phytophthora ramorum on the west coast of the United States of America. Phytopathology 99(6):739–749

Rabbinge R (1993) The ecological background of food production. In: Ciba foundation symposium. Wiley Online Library, pp 2–2

Rakotonindraina T, Chauvin J-E, Pellé R, Faivre R, Chatot C, Savary S, Aubertot J-N (2012) Modeling of yield losses caused by potato late blight on eight cultivars with different levels of resistance to Phytophthora infestans. Plant Dis 96(7):935–942

Regniere J (2011) Invasive species, climate change and forest health. In: Forests in development: a vital balance. Springer, Dordrecht, pp 27–37

Régnière J, Powell J, Bentz B, Nealis V (2012) Effects of temperature on development, survival and reproduction of insects: experimental design, data analysis and modeling. J Insect Physiol 58 (5):634–647

Richerzhagen D, Racca P, Zeuner T, Kuhn C, Falke K, Kleinhenz B, Hau B (2011) Impact of climate change on the temporal and regional occurrence of Cercospora leaf spot in Lower Saxony. J Plant Dis Prot 118(5):168–177

Riesenfeld CS, Schloss PD, Handelsman J (2004) Metagenomics: genomic analysis of microbial communities. Annu Rev Genet 38:525–552

Robert C, Bancal M-O, Lannou C, Ney B (2005) Quantification of the effects of Septoria tritici blotch on wheat leaf gas exchange with respect to lesion age, leaf number, and leaf nitrogen status. J Exp Bot 57(1):225–234

Rodriguez RJ, Henson J, Van Volkenburgh E, Hoy M, Wright L, Beckwith F, Kim Y-O, Redman RS (2008) Stress tolerance in plants via habitat-adapted symbiosis. ISME J 2(4):404
Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburn P, Antle JM, Nelson GC, Porter C, Janssen S (2013) The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric For Meteorol 170:166–182
Rossi V, Giosuè S, Caffi T (2009) Modelling the dynamics of infections caused by sexual and asexual spores during Plasmopara viticola epidemics. J Plant Pathol 91:615–627
Rouse D (1988) Use of crop growth-models to predict the effects of disease. Annu Rev Phytopathol 26(1):183–201
Runion G, Curl E, Rogers H, Backman P, Rodriguez-Kabana R, Helms B (1994) Effects of free-air CO2 enrichment on microbial populations in the rhizosphere and phyllosphere of cotton. Agric For Meteorol 70(1–4):117–130
Saha S, Moorthi S, Wu X, Wang J, Nadiga S, Tripp P, Behringer D, Hou Y-T, H-y C, Iredell M (2014) The NCEP climate forecast system version 2. J Clim 27(6):2185–2208
Salam MU, MacLeod WJ, Salam KP, Maling T, Barbetti MJ (2011) Impact of climate change in relation to ascochyta blight on field pea in Western Australia. Australas Plant Pathol 40(4):397
Salinari F, Giosuè S, Rossi V, Tubiello FN, Rosenzweig C, Gullino ML (2007) Downy mildew outbreaks on grapevine under climate change: elaboration and application of an empirical-statistical model. EPPO Bull 37(2):317–326
Sandermann JH (2000) Ozone/biotic disease interactions: molecular biomarkers as a new experimental tool. Environ Pollut 108(3):327–332
Savary S, Willocquet L (2014) Simulation modeling in botanical epidemiology and crop loss analysis. Plant Health Instruct. https://doi.org/10.1094/PHI-A-2014-0314-01
Savary S, Teng PS, Willocquet L, Nutter FW Jr (2006) Quantification and modeling of crop losses: a review of purposes. Annu Rev Phytopathol 44:89–112
Scherm H (2000) Simulating uncertainty in climate–pest models with fuzzy numbers. Environ Pollut 108(3):373–379
Scherm H (2004) Climate change: can we predict the impacts on plant pathology and pest management? Can J Plant Pathol 26(3):267–273
Seherm H, Coakley SM (2003) Plant pathogens in a changing world. Australas Plant Pathol 32 (2):157–165
Shabani F, Kumar L (2013) Risk levels of invasive Fusarium oxysporum f. sp. in areas suitable for date palm (Phoenix dactylifera) cultivation under various climate change projections. PLoS One 8(12):e83404
Sparks AH, Forbes GA, Hijmans RJ, Garrett KA (2014) Climate change may have limited effect on global risk of potato late blight. Glob Chang Biol 20(12):3621–3631
Stein LD, Mungall C, Shu S, Caudy M, Mangone M, Day A, Nickerson E, Stajich JE, Harris TW, Arva A (2002) The generic genome browser: a building block for a model organism system database. Genome Res 12(10):1599–1610
Stern N (2008) The economics of climate change. Am Econ Rev 98(2):1–37
Stone JK, Coop LB, Manter DK (2008) Predicting effects of climate change on Swiss needle cast disease severity in Pacific Northwest forests. Can J Plant Pathol 30(2):169–176
Sturrock R, Frankel S, Brown A, Hennon P, Kliejunas J, Lewis K, Worrall J, Woods A (2011) Climate change and forest diseases. Plant Pathol 60(1):133–149
Sutherst R, Maywald G, Kriticos D (2007) CLIMEX version 3: user's guide
Sutherst RW, Constable F, Finlay KJ, Harrington R, Luck J, Zalucki MP (2011) Adapting to crop pest and pathogen risks under a changing climate. Wiley Interdiscip Rev Clim Chang 2 (2):220–237
Swiecki TJ, Bernhardt EA (2016) Sudden oak death in California. In: Insects and diseases of mediterranean forest systems. Springer, Cham, pp 731–756
Tatusov RL, Galperin MY, Natale DA, Koonin EV (2000) The COG database: a tool for genome-scale analysis of protein functions and evolution. Nucleic Acids Res 28(1):33–36

Thompson J (2007) The mysterious demise of an ice-age relic: exposing the cause of yellow-cedar decline. Science findings 93 Portland, OR: US Department of Agriculture, Forest Service, Pacific Northwest Research Station 5, p 93

Thompson BG, Drake BG (1994) Insects and fungi on a C3 sedge and a C4 grass exposed to elevated atmospheric CO2 concentrations in open-top chambers in the field. Plant Cell Environ 17(10):1161–1167

Tiedemann A, Firsching K (2000) Interactive effects of elevated ozone and carbon dioxide on growth and yield of leaf rust-infected versus non-infected wheat. Environ Pollut 108 (3):357–363

Uchôa CN, Pozza EA, Albuquerque KS, Moraes WS (2012) Relationship between temperature and leaf wetness in Black Sigatoka monocycle. Summa Phytopathol 38(2):144–147

Van der Plank JE (2013) Plant diseases: epidemics and control. Elsevier, New York

Van Mantgem PJ, Stephenson NL, Byrne JC, Daniels LD, Franklin JF, Fulé PZ, Harmon ME, Larson AJ, Smith JM, Taylor AH (2009) Widespread increase of tree mortality rates in the western United States. Science 323(5913):521–524

Vary ZM, Ewen McElwain CJ, Doohan MF (2015) The severity of wheat diseases increases when plants and pathogens are acclimatized to elevated carbon dioxide. Glob Chang Biol 21 (7):2661–2669

Vaughan MM, Huffaker A, Schmelz EA, Dafoe NJ, Christensen S, Sims J, Martins VF, Swerbilow J, Romero M, Alborn HT (2014) Effects of elevated [CO2] on maize defence against mycotoxigenic F usarium verticillioides. Plant Cell Environ 37(12):2691–2706

Venette RC, Kriticos DJ, Magarey RD, Koch FH, Baker RH, Worner SP, Gómez Raboteaux NN, McKenney DW, Dobesberger EJ, Yemshanov D (2010) Pest risk maps for invasive alien species: a roadmap for improvement. Bioscience 60(5):349–362

Welch S, Croft B, Brunner J, Michels M (1978) PETE: an extension phenology modeling system for management of multi-species pest complex. Environ Entomol 7(4):487–494

Whish JP, Herrmann NI, White NA, Moore AD, Kriticos DJ (2015) Integrating pest population models with biophysical crop models to better represent the farming system. Environ Model Softw 72:418–425

Willocquet L, Savary S, Fernandez L, Elazegui F, Teng P (2000) Development and evaluation of a multiple-pest, production situation specific model to simulate yield losses of rice in tropical Asia. Ecol Model 131(2–3):133–159

Willocquet L, Savary S, Fernandez L, Elazegui F, Castilla N, Zhu D, Tang Q, Huang S, Lin X, Singh H (2002) Structure and validation of RICEPEST, a production situation-driven, crop growth model simulating rice yield response to multiple pest injuries for tropical Asia. Ecol Model 153(3):247–268

Willocquet L, Elazegui FA, Castilla N, Fernandez L, Fischer KS, Peng S, Teng PS, Srivastava R, Singh H, Zhu D (2004) Research priorities for rice pest management in tropical Asia: a simulation analysis of yield losses and management efficiencies. Phytopathology 94 (7):672–682

Willocquet L, Aubertot J, Lebard S, Robert C, Lannou C, Savary S (2008) Simulating multiple pest damage in varying winter wheat production situations. Field Crop Res 107(1):12–28

Wong P, Mead J, Croff M (2002) Effect of temperature, moisture, soil type and Trichoderma species on the. Australas Plant Pathol 31(3):253–257

Yonow T, Zalucki M, Sutherst R, Dominiak B, Maywald G, Maelzer D, Kriticos D (2004) Modelling the population dynamics of the Queensland fruit fly, Bactrocera (Dacus) tryoni: a cohort-based approach incorporating the effects of weather. Ecol Model 173(1):9–30

Zadoks J (1971) Systems analysis and the dynamics of epidemics. Phytopathology

Zadoks JC, Schein RD (1979) Epidemiology and plant disease management. Epidemiology and plant disease management