ANNUAL REVIEWS

Annual Review of Phytopathology

Climate Change Effects on Pathogen Emergence: Artificial Intelligence to Translate Big Data for Mitigation

K.A. Garrett,[1,2,3] D.P. Bebber,[4] B.A. Etherton,[1,2,3] K.M. Gold,[5] A.I. Plex Sulá,[1,2,3] and M.G. Selvaraj[6]

[1]Plant Pathology Department, University of Florida, Gainesville, Florida, USA; email: karengarrett@ufl.edu

[2]Food Systems Institute, University of Florida, Gainesville, Florida, USA

[3]Emerging Pathogens Institute, University of Florida, Gainesville, Florida, USA

[4]Department of Biosciences, University of Exeter, Exeter, United Kingdom

[5]Plant Pathology and Plant Microbe Biology Section, School of Integrative Plant Sciences, Cornell AgriTech, Cornell University, Geneva, New York, USA

[6]The Alliance of Bioversity International and the International Center for Tropical Agriculture (CIAT), Cali, Colombia

Annu. Rev. Phytopathol. 2022. 60:357–78

First published as a Review in Advance on June 1, 2022

The *Annual Review of Phytopathology* is online at phyto.annualreviews.org

https://doi.org/10.1146/annurev-phyto-021021-042636

Keywords

artificial intelligence, climate change, decision support, geographic risk, plant disease, remote sensing

Abstract

Plant pathology has developed a wide range of concepts and tools for improving plant disease management, including models for understanding and responding to new risks from climate change. Most of these tools can be improved using new advances in artificial intelligence (AI), such as machine learning to integrate massive data sets in predictive models. There is the potential to develop automated analyses of risk that alert decision-makers, from farm managers to national plant protection organizations, to the likely need for action and provide decision support for targeting responses. We review machine-learning applications in plant pathology and synthesize ideas for the next steps to make the most of these tools in digital agriculture. Global projects, such as the proposed global surveillance system for plant disease, will be strengthened by the integration of the wide range of new data, including data from tools like remote sensors, that are used to evaluate the risk of

plant disease. There is exciting potential for the use of AI to strengthen global capacity building as well, from image analysis for disease diagnostics and associated management recommendations on farmers' phones to future training methodologies for plant pathologists that are customized in real-time for management needs in response to the current risks. International cooperation in integrating data and models will help develop the most effective responses to new challenges from climate change.

INTRODUCTION

Weather: conditions in the atmosphere, including temperature, precipitation, and humidity

Climate: long-term weather patterns at a location, including mean conditions, variability in conditions, and extreme conditions

Artificial intelligence (AI): intelligence exhibited by machines allowing them to respond to input and give a response toward a defined goal

Decision support systems (DSSs): computer programs to support decision-making based on available data and priorities

Regression analysis: method for estimation of the relationship between a response variable and one or more predictor variables

Big data: data sets large enough to challenge older computing systems, and sometimes assembled with differing collection processes

Plant disease has major effects on agricultural crop yield, quality, and safety (121, 126) and invasive pathogens threaten natural systems, such as forests, globally. Weather factors like temperature and moisture availability are well-known for their role in plant disease risk. Seasonal and interannual variations in weather offer plenty of challenges for disease management decision-making. Climate change adds to these challenges by shifting the range of weather scenarios at most locations globally, often producing new weather patterns that locations have not previously experienced. Climate change effects on plant disease have been a focus of interest for decades, but data availability and modeling options have often been a limiting factor in analyses (13, 34, 62, 76, 78, 115, 122). Invasions of plant pathogens into new regions are also an ongoing threat (30, 50), and climate change has the potential to increase invasion risk. The effects of climate change and pathogen invasions converge with greater human populations and demands for resources as well as with societal disruptions due to human epidemics, political instability, and conflicts.

At the same time, technologies with the potential to support plant disease mitigation continue advancing. Currently, many national programs and institutions are emphasizing the development of artificial intelligence (AI) across scientific disciplines. AI offers opportunities for improving several components of systems for plant disease management (**Figure 1**). The potential applications include improved decision support systems (DSSs) from on-farm to global policy making, crop breeding, microbiome formulation, postharvest management, robotic management of disease, and systems to support capacity building for plant health personnel globally. Discussions of AI often feature both the great possibilities and the potential hype surrounding AI. Previous periods of AI hype were followed by so-called AI winters when scientists and institutions lost interest in AI as promises were not realized. Will plant pathology soon move into an AI winter or will the promises of AI be realized in the short run? Some familiar aspects of AI, such as regression analysis, are likely to remain important tools in plant pathology into the future. It remains to be seen what roles less familiar aspects of AI, such as robotic disease management, will play in the future in agricultural production, where profit margins may be small. It also remains to be seen whether benefits from large-scale data integration can be spread equitably and translated effectively for people globally, including those who experience food insecurity and/or depend on agriculture for their livelihoods.

In this synthesis, we address current and future potential applications of AI to translate expanding big data availability for mitigation of emerging plant diseases. Understanding and predicting changes in disease risk are important goals for climate change adaptation of agriculture and ecosystem management. The more common availability of big data from global climate and remotely sensed data to genomics and phenomics can support mitigation of these risks. We present an overview of how climate change is affecting disease risk, new AI options for understanding and addressing threats to plant health, the potential for remote sensing, and considerations for making the benefits of new analyses widely available. We hope that the new potential of tools for translating data to inform disease management and supporting global cooperation will inspire and spark the imagination of the next generation of plant pathologists.

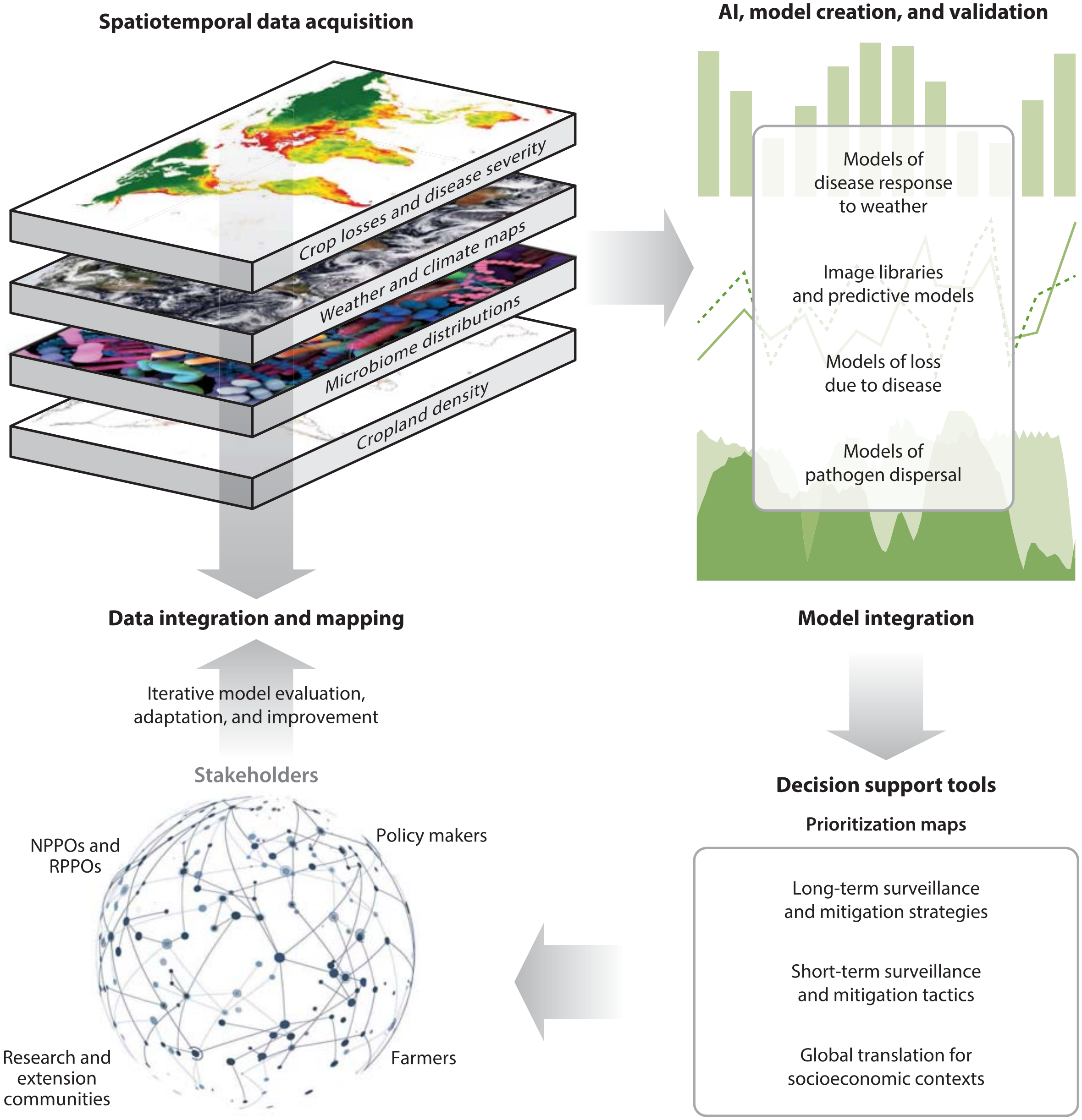

Figure 1

Artificial intelligence (AI) can integrate key spatiotemporal data in models of the effects of climate on emerging disease risk, generate maps of geographic priorities for surveillance and mitigation strategies, and translate these analyses in practical tools for stakeholders. A repeating cycle of integration and analyses can fine-tune responses in a globally coordinated system for climate change adaptation. Abbreviations: NPPOs, national plant protection organizations; RPPOs, regional plant protection organizations.

CLIMATE CHANGE EFFECTS ON PLANT DISEASE

Two related conceptual frameworks can help us consider climate change impacts on plant disease risk. First, the disease triangle describes the interactions between the pathogen(s), the plant host(s), and the environment in causing plant disease (56). Host–pathogen interactions include the virulence of the pathogen against particular host genotypes; host–environment interactions include the role of drought stress in promoting disease; and pathogen–environment interactions include the role of temperature in determining rates of pathogen life-cycle processes like growth within the host or spore germination. To fully understand and predict climate change effects on plant disease we must, theoretically, understand not only the details of these interactions and processes (63) but also the ways in which the climate will change in the future. Second, the biotic–abiotic–migration (BAM) model (141) states that species distributions are determined by regions with suitable availability of resources (susceptible hosts), environmental conditions (climate), and the ability of the species to reach them (dispersal). In the BAM framework, the geographical locations where these three regions intersect are where the species will be found, and climate change could influence all three (13).

Remote sensing: use of non-ground-based imaging systems to obtain information about processes and events

Making projections of future plant disease risks under climate change requires models that link responses of pathogens and hosts to climatic variables with estimates of past, current, and future climates. The estimation of microclimates experienced by organisms based on large-scale climate data is itself a complex process (15, 24). Understanding current (4) and future (124) host plant distributions is another complex component of future risk. Here, we focus on the responses of fungi and oomycetes to climate change, the pathogen–environment side of the disease triangle, but climate is also important for other pathogen groups (77).

The range of models used in plant disease epidemiology, from relatively simple statistical abstractions of relationships between climate and disease to detailed mathematical descriptions of life-cycle processes, mirrors that found in species distribution modeling within the discipline of biogeography (44). Plant pathogens have life cycles that involve infection of the host, growth within the host, and dispersal to new hosts. Each process is affected by climate and thus by climate change. The rust fungi, order Pucciniales (Basidiomycota), are important plant pathogens of agriculture and forestry and often exhibit complex life cycles with alternate hosts and overwintering stages connected by the dispersal of a range of spore types. Each stage can be variously affected by temperature, relative humidity, precipitation, wind, and sunlight, making modeling of climate impacts potentially complex. In a simple infection model for leaf stem rust (*Puccinia graminis*) that considered only the infection of leaves by germinating urediniospores (84), infection occurred only when leaves were wet and under high light availability, with a rate dependent on temperature. A more complex model considered not only the infection process but also UV and frost effects on spore survival, temperature-dependent spore production, wind- and turbulence-driven spore release and dispersal, and wet and dry deposition of spores onto crops (119). When driven by climate projections, both models found that future disease risk was determined by leaf surface wetness and temperature responses of infection. In the complex model, changing probabilities of long-distance dispersal were of secondary importance. Another comparison of the simple infection model with a more complex, spatially explicit dispersal model, this time for wheat stripe (yellow) rust (caused by *Puccinia striiformis* f. sp. *tritici*), found good agreement between both models with indirectly observed disease incidence (105).

Infection risk has been called the gateway to rust epidemics (82) and is thus the focus of many analyses of climate change impacts on disease risk. Leaf surface wetness, or high relative humidity, is a prerequisite for spore germination and penetration of the leaf surface for many fungal and oomycete pathogens. Climate change influences moisture regimes and thus disease risk. A fascinating paleoecological study spanning a 49,600-year period illustrates the role of moisture as a limiting factor in plant disease (155) in the Atacama Desert, Chile. Contemporary examples confirm an important role for moisture, for example, in the abundance and species richness of fungal plant pathogens in the phyllosphere (31) and in the elevational shift of white pine blister rust (*Cronartium ribicola*) in the Sierra Nevada mountain range in California as the climate warmed and dried over recent decades (48).

Where moisture is nonlimiting, temperature-dependent infection rates become the primary driver of disease risk. In soils, temperature is the most important determinant of fungal distributions in general (151) and fungal pathogen distributions in particular (42). A dearth of distribution data has hampered our understanding of how different climate drivers influence plant disease (13). However, a recent analysis of historical agricultural data across China provides strong evidence that changing temperatures exert the strongest control over pest and disease impacts, with climate change projected to double the relative area affected by pests and diseases by the end of the twenty-first century under a high emissions scenario (152). Chaloner et al. (28) collated experimentally determined temperature responses of several biological processes (e.g., growth in culture, infection rate, disease development, spore germination) for hundreds of fungal and oomycete plant pathogens, then used these to project infection risk for twelve crops under several climate change scenarios (29). Disease risk was compared to projected crop yield, revealing latitudinal shifts in both, finding that where climate change could improve crop yields, disease pressure will increase, and vice versa. The authors compared infection models with and without moisture limitation, finding little difference in regional-scale estimates between the two. Moisture could become a limiting factor in some regions under climate change, but future humidity and rainfall projections are far less well constrained than temperature projections (73). Although the effects of climate change on plant–pathogen interactions are extremely complex and both climate projections and climatic controls on biological processes remain poorly understood, observational data and models suggest two broad conclusions: first, that temperature is usually the most important determinant of disease risk and, second, that in locations where plants will benefit from climate change, their pathogens will also tend to benefit.

Machine learning: development of a new structure by algorithms, such as a classification system for plant images as healthy or symptomatic

Ensemble models: models that combine the predictions of multiple models, often performing better than the best individual model

ARTIFICIAL INTELLIGENCE: OVERVIEW OF CONCEPTS AND POTENTIAL

Machine Learning

Plant pathology has used statistical methods extensively for decades, including methods like regression analysis that are generally considered part of machine learning. Machine learning can be thought of as encompassing statistical methods in general as well as providing new approaches, expanding to prediction and classification using massive data sets such as images and videos. Older statistical methods often emphasize inference and estimation, whereas newer machine learning methods often emphasize prediction (25, 51, 72); of course, in many cases, scientists and practitioners want outcomes to be both explainable and predictable. Common statistical applications in plant pathology over the years that emphasize estimation and attribution include the analysis of designed experiments in which disease severity may respond to experimental treatments like differing host genotypes, environmental variables, and pathogen traits. The goals of these experiments would often include understanding the mechanisms underlying the relationships between predictors such as host genotype and responses such as disease severity. Other types of machine learning methods that are newer to plant pathology are often used in contexts where prediction is the main goal and there may be less emphasis on estimation. Examples where prediction is the emphasis would include categorizing images as indicating the presence or absence of disease.

Machine learning has active communities developing improved algorithms, driven by a wide range of applications as well as contests and other opportunities to directly compare algorithm performance. The structure of machine learning algorithms often facilitates direct comparison of the performance of different algorithms and ensemble models in applications. For example, many types of machine learning algorithms were compared in an analysis of surveillance strategies for *Xylella fastidiosa* (96). Algorithms often include wrappers that can be used to find optimal values of hyperparameters and other parameters and to build new models based on the shortcomings of earlier models. Cross-validation is used to evaluate predictions for data that were not used in learning the model, where it is important to structure cross-validation correctly in terms of the data sampling structure and potential confounding factors (11, 51).

Hyperparameters: assigned values that control the fitting process of machine learning algorithms, such as the number of iterations

Deep learning: subset of machine learning that develops predictions based on multiple (deep) layers of representations of data

Neural networks: potential components of deep learning layers, named because their structure has been inspired by human neuron connections

Digital agriculture: agricultural systems that incorporate digital devices to collect and analyze spatiotemporal data to guide actions

Value of information: the improvement in outcomes when decision-making is based on information compared to outcomes without the information

All the options for optimization in machine learning also have the potential to result in overfitting, i.e., constructing a predictive model that is overly specific to the data used for learning. A common weakness in machine learning is the inability to perform with new types of data. This is a particular concern in the context of climate change, where new combinations of hosts, pathogens, and environments occur. Any type of prediction of complex systems will be challenged by situations that are not represented well in the data used in formulating models, i.e., that lack statistical support. Global analyses generally include a good share of interpolation and extrapolation, but do the same methods that provide interesting global perspectives also provide predictions that are useful for finer-scale economic decision-making?

Advances in deep learning methods have made new options available for extremely detailed data sets such as images and videos (133) as well as weather prediction (131). Neural networks have also been used for decades in plant pathology, such as in epidemiology (43) and remote sensing (160). Now greater computational speed broadens the opportunities for using deep learning. Deep learning methods also have some potential limitations, such as their need for large data sets, or data hungriness, their weaknesses in dealing with changing conditions, their limited ability to integrate with past knowledge, and that they generally provide analysis of correlation rather than causation (95). Combining deep learning methods with other approaches has the potential to provide the best of both worlds.

Robotics

Digital agriculture also has the potential to incorporate robotics into disease management. Ground robots may offer value to disease management through both automated detection and targeted management. Proximal sensing systems deployed in the field on ATVs, tractors, or autonomous rovers with onboard computer vision can aid experts in monitoring larger areas than human scouts could feasibly cover (20, 71, 89). Applying UV-B light supports powdery mildew management and automated light application has been implemented for high-value crops such as grape and strawberry (111, 145). Robotics may be useful for targeted application of pesticides, perhaps especially for high-value crops like grapes (108). There are interesting possibilities for epidemic calculations to be incorporated in decision-making by digital agricultural machinery in the field or postharvest. These might include detecting disease symptoms, evaluating how far from the observed infection there may already be latent infection, and evaluating disease risk based on data about recent weather, crop architecture and its effects on microclimate, and other factors. Sequential sampling schemes could be automated and implemented based on where disease is detected in the first round of sampling, in combination with other predictor variables, considering the value of information for decision-making.

Unmanned aerial vehicles (UAVs), or drones, are another interesting option for collecting data such as images (91, 92), microbes (128), plant tissue samples, and other data from sensors. UAVs also have the potential to perform field operations based on real-time decisions guided by the data they collect. However, current applications in agriculture may have limitations because of regulations and the limited availability of technically skilled operators as well as the need for economic returns on investments. The use of UAVs for collecting phenotype images in crop breeding

(136), where high precision can readily give a substantial economic benefit, seems likely to become widely established.

THE PLANT DISEASE RESEARCH VALUE CHAIN RESPONDING TO THE CHALLENGES OF GLOBAL CHANGE

Research in plant pathology constitutes a value chain providing solutions to new challenges from global change, where AI can make responses to emerging diseases more efficient, including early detection of emergence (**Figure 2**). For plant pathosystems, digital twins can be constructed with

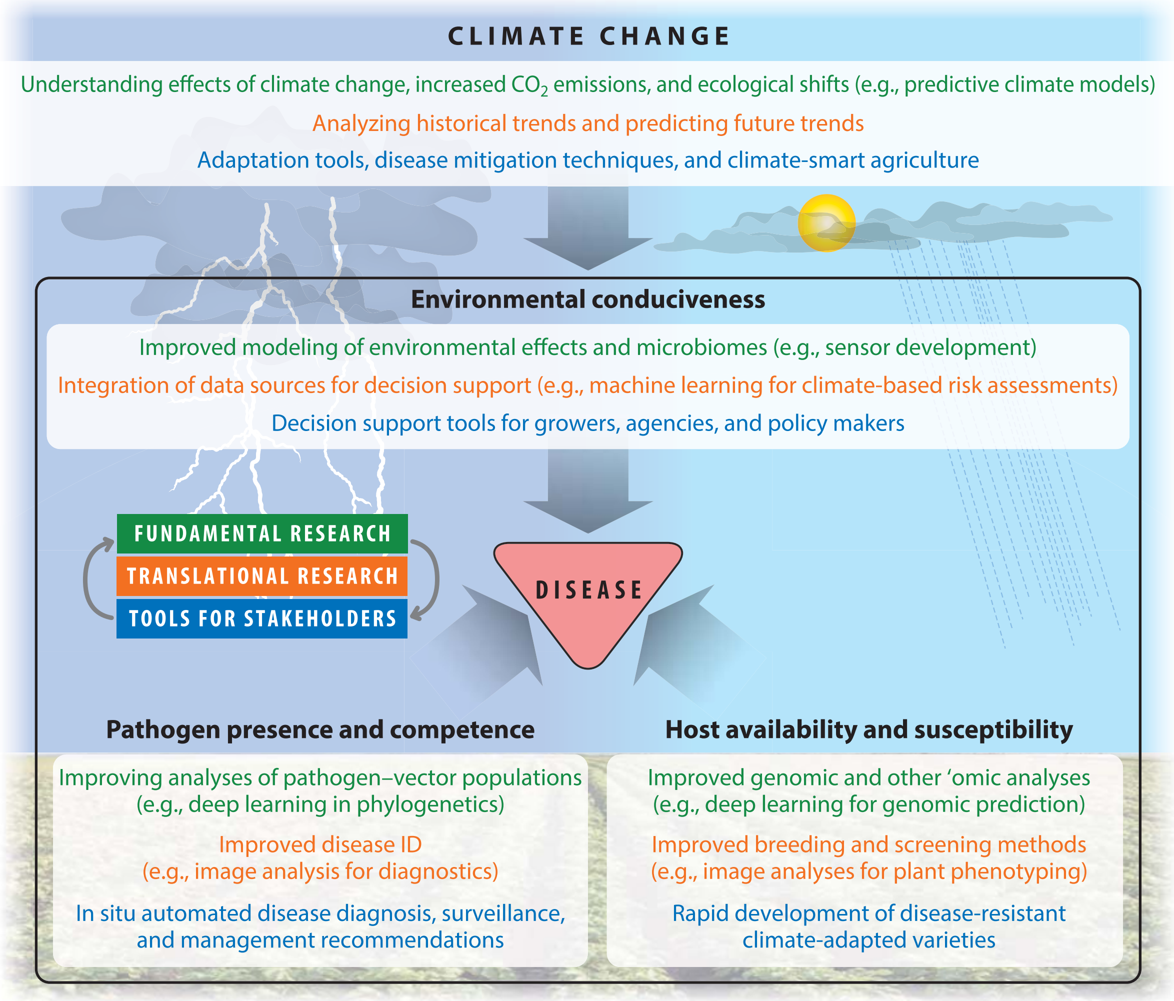

Figure 2

Plant health research can be thought of as a value chain providing solutions for each aspect of the disease triangle and their interactions. Artificial intelligence supports the understanding of the effects of climate change on these interacting factors and provides tools for research translation to products useful for stakeholders, with feedback from stakeholder testing back to research programs. The resilience and efficiency of this research value chain will determine whether effective mitigation and adaptation to emerging diseases occur.

key data and models that can duplicate the main processes in a system, even for extensive systems (12). For example, one exciting challenge will be modeling microbiome interactions and understanding how to manage them to support plant health (118, 146), where a great number of weak associations is one issue for inference, as discussed by Efron (51).

In crop breeding for disease resistance to adapt to new disease risks, models support genomics-assisted breeding (149) and deployment of resistance genes (45). A major bottleneck is the time required for variety selection and the limited availability of high-throughput field phenotyping tools to accurately assess phenotypic expressions. Machine learning has made advances in image analysis for phenotyping (33, 93). Phenomics-assisted disease resistance breeding has advanced for potato late blight (47, 66) and viruses (67, 117). CGIAR breeding programs routinely use deep learning and machine learning as the basis for models to accurately classify breeding lines with resistance to potato late blight (66), Rice hoja blanca virus (41), and banana *Xanthomonas* wilt (132), potentially reducing disease scoring time from several days to hours. With developments in hardware–software technologies, e.g., sensor development and quantum computing, onboard image/data processing and real-time analysis will become a reality.

DSSs help growers make evidence-based and precise decisions, focusing on optimizing productivity and maximizing economic returns on investments. DSSs can start with simple models and improve with incorporation of more information as it becomes available. Potato late blight has a long history of weather-based modeling to support within-season management decisions with straightforward models. For example, the LATE BLIGHT model, initially developed to simulate late blight epidemics in the Andes (6, 7), was found to perform well over a range of other tropical environments (5, 17). Late blight models have been reworked to project late blight risk under coarse-grained climate change scenarios (143), and for finer temporal scales, the BLIGHTSIM model was developed to take into account diurnal fluctuating temperatures (103). Functionally represented weather time series are an opportunity to use detailed weather data (135). Under rapid climate change, new weather patterns may make DSSs more challenging and also potentially more important (61). Postharvest protection of crop products can also be directed by DSSs to optimize storage and protect consumer health through supply chains, such as via prediction of mycotoxin content (40). Automated handling of fruits such as apples can also be based on analysis of fruit images, with the potential for improved management with incorporation of more information about disease risk factors in the fields where fruit was harvested.

For regional management and surveillance, understanding of the geographic structure of weather-based risk through machine learning can be integrated with other risk factors to guide surveillance and regional mitigation under climate change (96, 139). Risk-based surveillance considers the likely epidemic spread of disease (113, 114). Early in invasions, there are opportunities to contain invasions, motivating optimization based on limited information (38). Integrating information about the potential for coordinated management and likely individual management decisions can also guide regional optimization and decision-making (58, 59). As another example of integration, *X. fastidiosa* was detected in almond orchards by synergic use of an epidemic spread model and remotely sensed plant traits (26). Integration of information from farmers using tools such as Nuru (101) for disease diagnosis is another exciting opportunity for citizen science contributions to disease surveillance.

Strengthening human interfaces with AI can make systems more effective. Explainable AI (XAI) is an interesting option for further development in plant pathology applications (1, 68, 130). The black-box nature of some machine learning approaches, such as common deep learning methods, has inspired attention to how to modify methods to both help provide people using the methods with more insights into systems and incorporate more knowledge from users (130). Clever Hans effects, named after the horse Clever Hans who responded to cues from trainers rather than actually answering the questions he was supposed to be able to answer, can be observed with deep neural networks. Similarly, machine learning may be driven by confounding factors in the data. For example, suppose in a training data set one disease generally occurs with overcast skies but another disease occurs in bright sunlight, or one disease might have been photographed on younger plants while another was photographed on older plants. These confounding visual effects could be important parts of the model developed by the machine learning algorithm. In XAI, coactive learning with humans is used to revise models and attempt to detect and explain potential confounding factors, which may be even more important under changing weather conditions (125). XAI aims to explain the basis for a decision or prediction, although the explanation may be convoluted to non–data scientists. XAI should aim to be understandable to non–data scientists, making AI and machine learning more transparent to the general public (87).

Text mining: automated extraction of information from text, such as detecting increased use of words referring to disease

Human health offers useful examples of efforts to use AI for disease management. Google Flu Trends was used in online searches to predict influenza outbreaks and was criticized for big data hubris, the idea that data quantity can make up for data quality, when its predictions were not effective (83). Machine learning has proven useful in image analysis for disease diagnostics (137). In public health and precision medicine, similar issues as those for plant disease are noted, including the inherent bias when disease is noted but health is not, with even greater privacy issues (100, 120). Naudé (104) concluded that AI was not impactful in the early response against COVID-19.

AI is likely to speed up the processes by which people achieve their goals; outcomes are still limited by human good judgment and imagination and individuals' access to resources. For example, speeding up processes in plant pathology could result in more efficient production of megavarieties that are vulnerable to rapid pathogen spread when resistance genes are overcome. Systems may more efficiently externalize costs. Targeting projects for the greatest benefits may be more efficient, but targeting might be so efficient that considerations not explicitly quantified are lost (23, 60). There is also the potential for more effective spread of disinformation and the possibility of misuse of information in agroterrorism.

NEW TYPES OF DATA AND MODELS BECOMING AVAILABLE

A range of new data types are becoming available through remote sensing of plant disease (110), from volatile profiles (85) to text mining (127). We may be approaching what is possible with visual analysis of disease symptoms, with the potential to improve analyses using sensors (18). Image data collections support disease classification models (**Figure 3**) (99), such as a library of foliar diseases of wheat (21) or cassava disease (120a). As remote sensing becomes a more commonly used tool, images of larger-scale epidemics may also be assembled in epidemic image collections.

Remote sensing is unique among disease detection methods in its ability to offer passive monitoring. Most risk assessment methods require some sort of understanding of underlying disease distribution for appropriate calibration; for example, systems that issue action thresholds based on initial detection, whether via molecular assays or smartphone apps, all require a human to first find and observe the disease in the environment. Even in small-scale production systems, most fields are too large for growers to cost-effectively monitor daily or weekly. Remote sensing can inform plant disease risk assessment by offering the capacity for monitoring at previously unachievable scales, filling gaps in space and time between labor-intensive field measurements, while reducing uncertainty in downstream analyses and management decision-making.

Advances in remote sensing will enable high temporal- and spatial-resolution monitoring that can be used to efficiently deploy high-accuracy ground diagnostics and remediation activities to diseased plants before epidemics emerge. Imaging spectroscopy, also known as hyperspectral

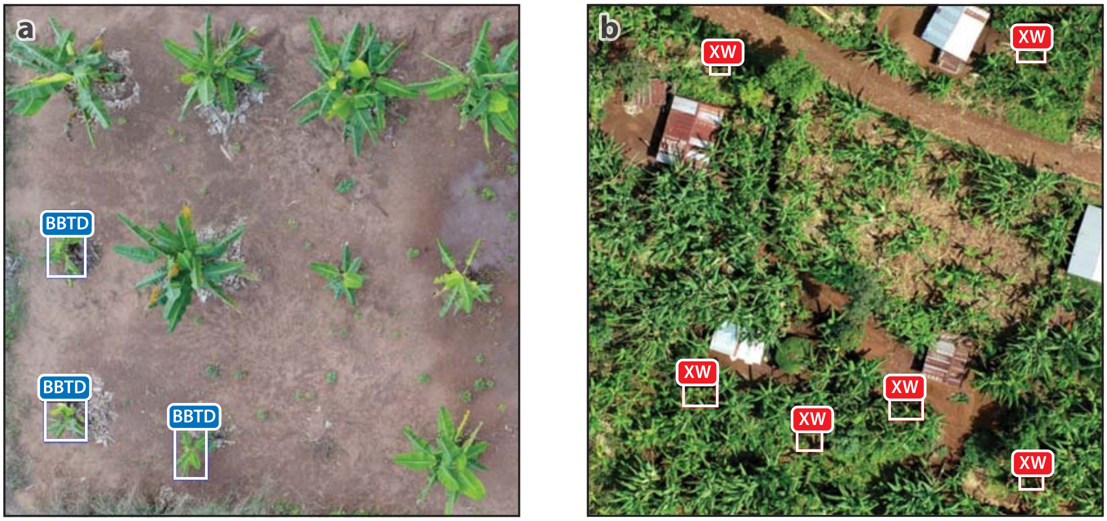

Figure 3

Illustration of RGB-based deep learning for detection of (*a*) banana bunchy top disease (BBTD) symptoms and (*b*) banana *Xanthomonas* wilt (XW) symptoms in a mixed-complex African landscape. Adapted from Reference 132.

imaging, can quantify plant disease in terms of variation in solar radiation interactions with leaves and canopies. Imaging spectroscopy in the visible to shortwave infrared light range (VSWIR; 400–2,400 nm) can quantify chemistry in soil, rock, and vegetation based on the interaction of light with chemical bonds (39). This underlying capacity is what enables the use of imaging spectroscopy for early and nondestructive biotic stress detection in both natural and agroecosystems (65). Both beneficial (142) and parasitic (93) plant–microbe interactions impact a variety of plant traits that can be sensed by aerial and spaceborne imaging spectrometers (92, 107). Plant pathogens can change foliar composition, such as through production of systemic effectors or secondary metabolites, or by the physical presence of pathogen structures, such as hyphae and spores. Broadband and multispectral methods relying on visible (400–700 nm) and near-infrared (700–1,000 nm) reflectance indices, such as the normalized difference vegetation index (NDVI), have been used to sense late-stage plant disease since the 1980s (75, 102). For example, NDVI is primarily sensitive to total overall greenness (i.e., green cover) and thus detects green vegetation dieback. Simple indices such as NDVI that are widely available both commercially and from space agencies are useful for general targeting and risk assessment but have proven insufficient for disease diagnosis, especially in multistress environments (35).

Changes in continuous, shortwave infrared (SWIR; 1,000–2,500 nm) wavelengths have proved valuable for plant disease sensing due to their sensitivity to a range of foliar properties (39), including nutrient content (64, 138, 153, 154, 157, 159), water (57), photosynthetic capacity (112), physiology (134), phenolics (80), and secondary metabolites (36, 37), that are all impacted by disease. Use of SWIR reflectance from satellites greatly improves disease detection in the absence of, and/or prior to, a greenness response (16, 49, 98). Historically, narrowband SWIR data have not been widely available from spaceborne systems. However, this will soon change. Forthcoming satellite systems with launches planned for the late 2020s such as the European Space Agency's Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) (106) and NASA's Surface Biology and Geology (SBG) (129) will revolutionize global imaging spectroscopy data availability. These systems will provide VSWIR hyperspectral imagery at high resolution (30 m) across the entire globe when launched later this decade. Taken as a constellation, these instruments will provide data at weekly or better intervals without cost and will, for the first time, democratize the availability of such powerful data products.

Integrating objective plant health assessments from these forthcoming, hyperspectral satellite systems into existing DSSs has the potential to improve risk and economic injury threshold assessment while providing a counterbalance to subjective human ratings without taking the ultimate decision-making away from the stakeholder (14). This will be particularly useful in regions most at risk for agri-food change disruptions and downstream impacts on food security and safety. For example, alert systems connected to remote sensing data could warn when vulnerable plant populations are under attack by pathogen, pest, or anthropogenic factors, identifying novel/emerging risks to both natural and agroecosystem function in the context of climate change and pathogen spread. This could have a revolutionary impact on low-income countries that cannot financially support intensive ground monitoring for emerging threats. Challenges for implementation may include unsupportive local governments, lack of equipment and support infrastructure, and preventative material export laws. Remote sensing with next-generation systems can offer a path around these historical challenges by funneling resources and expertise from high-income countries to global regions most in need.

Imagery from space agency satellites is an ideal foundation for risk assessment tools, as the data are free and any changes to accessibility are announced well in advance. But just because the data are freely available does not mean that they are universally accessible. For example, NASA's Airborne Visible and Infrared Imaging Spectrometer Next Generation (AVIRIS-NG) has opportunistically captured VSWIR imagery of almost one million acres of vineyards in California over the past 5 years during missions focused on nonagricultural objectives (147), but better tools and user interfaces for accessing, searching through, and processing archived imagery for nonexpert users will be essential for utilizing spaceborne data to their fullest potential. The key to achieving this goal will be interdisciplinary training and collaboration between plant pathologists and engineers, computer scientists, and remote sensing experts to build usable decision support and risk assessment systems for both researchers and stakeholders (70).

Biotic stress is the result of dynamic interactions between living organisms within ever-changing micro, meso, and macroclimates. The unique challenges associated with studying crop disease have yielded a discipline far behind other agricultural sensing domains, such as nutrition and water management, which have seen major advances at the satellite scale in recent years. Multiple diseases and abiotic stresses may occur in the same target sensing zone. Learning how to effectively distinguish these at scale is essential because mitigation resources are limited, and endemic versus invasive diseases require different urgency in response. It is unreasonable to expect hyperspectral satellites to perfectly differentiate all crop stresses at all target stages of assessment from the spaceborne resolution, but, for example, it has recently been established that abiotic and biotic stresses with similar visual appearance (i.e., wilting) but different origins have divergent spectral pathways, which is why spectroscopy can be used to differentiate between them (158). Understanding the capacity and limitations of spaceborne sensing on a pathosystem-by-pathosystem basis will be essential for appropriately using these forthcoming data streams and successfully integrating their outputs into existing decision support tools.

NEW POSSIBILITIES FOR INTEGRATING EPIDEMIOLOGICAL DATA TO UNDERSTAND CLIMATE CHANGE AND RESPONSES

Epidemiological Data for Climate Change Response

Decision-makers are expected to respond quickly to mitigate emerging diseases, despite the uncertainty surrounding new pathosystems. The perception of risk and prevalence of a disease (or climatic stressors) across a community can be pivotal in garnering regional collective action, although during the initial phase of an epidemic, decision-makers are less likely to respond (52, 94). In situations where there is high uncertainty regarding an emerging pest or pathogen, models can be used to forecast the disease's effects across a range of different scenarios. Statistical models can use data from remote sensors, climate data, soil sensors, vegetative spectral indices, etc., to establish general patterns of disease movement and can help identify which parameters may be the best predictors of disease dynamics (32, 79, 86). Many new agricultural tools incorporate the data from these sensors and use statistical learning to estimate the amount of disease within a population for a set of specific features (53, 148). For example, Ocimati et al. (109) constructed a map of areas in Africa that may be at high risk for *Xanthomonas* wilt of banana, using multiple regression analyses of the topographic, climate, and management features of a smaller region. Small et al. (140) created a system to substantiate the decisions of growers about when and how best to manage *Phytophthora infestans* infecting potato and tomato, using weather and geographic data.

Remote sensing data can improve existing DSSs by providing estimates of underlying disease distribution. For example, synergistic use of an epidemic spread model with airborne hyperspectral imagery improved *X. fastidiosa* mapping in almond (26). The incorporation of sensor data and statistical models is the basis for digital agriculture and the development of a DSS (32, 79, 148). These systems can help to quantify the fine details of an epidemic, although there are currently still many limitations to widely implementing DSSs, including access to frameworks and large data sets, adaptability across landscapes and pathosystems, and the cost of new infrastructure (8, 79). Changing ecosystems lead to uncertainty in patterns of dispersal and establishment. Many epidemiological models seek to address uncertainty about pathogens and weather systems and can model epidemics across a range of scenarios. For example, Cunniffe et al. (38) developed a model that accounts for the stochasticity of epidemics and allows users to specify pathosystem parameters, with the objective of informing policy and decision-makers. The more complex a system, the more useful models become, as they allow decision-makers to prioritize their resources.

Another frontier for integration of data and models is the incorporation of decision-making by farmers and other stakeholders, ideally in a system that both supports decision-making and effectively models the effects of management decisions on regional disease risk. Integration of data to support regional disease management decisions can be implemented through frameworks such as impact network analysis (**Figure 4**) (59). This approach provides scenario analysis for potential management options and uncertainty quantification to deal with the fact that all the data that would be useful for decision-making are rarely available. Components of scenario analyses can include analyses of host landscape structures in terms of a location's connectivity to the surrounding cropland (156) and key locations in trade networks for vegetative planting materials (2, 3, 22) as a first step for understanding spatial risk factors, improved iteratively as systems are better understood.

TRANSLATING DATA AND MODELING INTEGRATION TO SUPPORT MANAGEMENT GLOBALLY

The International Plant Protection Convention (IPPC), through the development and implementation of sanitary and phytosanitary measures and international standards created by 184 national plant protection organizations (NPPOs) and 10 regional plant protection organizations, provides trade-oriented approaches to protect plant health globally and regionally (**https://www.ippc.int/en/**) (27). The IPPC is one important global structure that supports coordinated responses to shifting disease risks in response to global change.

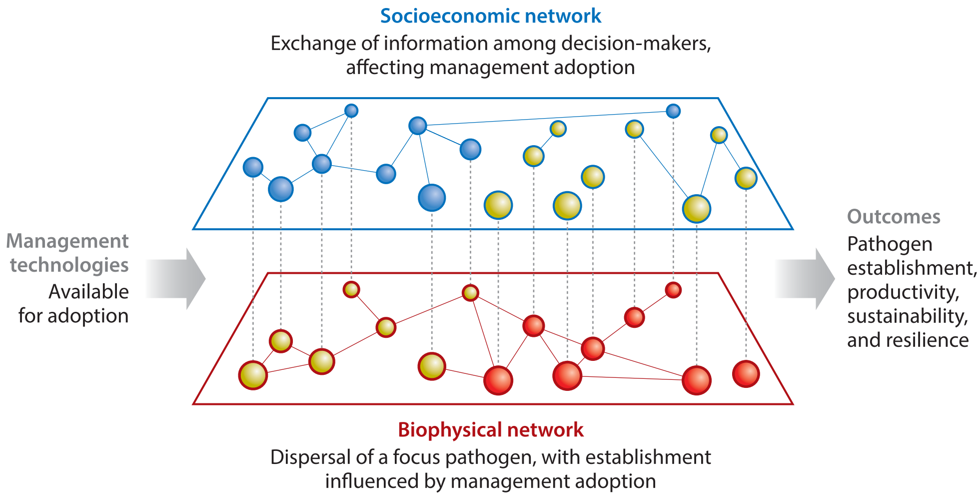

Figure 4

Incorporating disease management decision-making networks in an impact network analysis model. The socioeconomic network can represent farmers and/or agents in national plant protection organizations (NPPOs) deciding whether to use a new disease management technology (*blue nodes*) and influencing each other in that choice. The biophysical network can represent farms managed by these farmers and NPPOs in a geographic landscape, where the pathogen may spread and become established (*red nodes*) or not, as a function of how the disease is managed at each location. Adapted from Reference 59.

National and regional surveillance systems can build on translation from high-resolution data sets of climate variables (see 13) and information, often limited, about the current distribution of plant pathogens. Bioclimatic envelope models have used inductive modeling approaches or deductive models to assess current species distribution, potential habitat, and the ecological niche of invasive pathogens, and to project plant pathogen responses to changes in environmental conditions (29, 74, 116, 150). Models identifying key airborne dispersal routes can be used to inform surveillance of crop diseases (97). Integrative climatic models can also combine current, developed methods with innovative approaches (10, 55, 74). Methods can integrate multiple rule-based models following, for example, multicriteria decisions (29, 150). Uncertainty usually increases with climate change, but uncertainty quantification (or sensitivity analysis) of model outputs is often lacking, and validation of new model outputs is often not possible until some years later.

Innovative modeling approaches require incorporating substantial changes in the future distribution of plant hosts, vectors, and natural enemies (13). Modeling advances are required to consider the role of rapid changes in climate factors in the emergence, reemergence, distribution, and spread of plant pathogens (88). Models that integrate disease risk factors like cropland connectivity (156), weather conduciveness, airborne connectivity (97), trade, transport (10), and management (10) can provide insights into proactive approaches to prevent plant pathogen invasions and local buildup. Alert and warning systems are a critical component of early responses to the emergence of plant diseases (121). The Program for Monitoring Emerging Diseases exemplifies a global monitoring network reporting plant disease outbreaks since 1995. Models can also highlight current disease hot spots that are potential inoculum sources or highlight locations at risk (50, 88).

Fair Distribution of Benefits from Data and Models

The ability of countries to respond to invasive species varies across global landscapes (50). Countries with high scientific monitoring capacity, often in temperate regions, may detect and report the changes in pathogen distributions more readily, where reporting capacity may be a confounding factor when evaluating the effects of climate change (13). Uneven data availability across regions challenges big data approaches (10), especially regarding climate suitability of emerging pathogens (29). Intensive monitoring across all latitudes, particularly focusing on improvement for low- and middle-income countries, would strengthen the global capacity for surveillance (69).

Food system stakeholders, including smallholder farmers, have varying levels of scientific expertise. Social and political willingness to support plant health, and research and extension capacity, vary geographically (69). Communication and coordination are necessary among international and domestic markets, private and public sectors, and informal and formal trading systems (69, 90). The identification of regional weaknesses can help in prioritizing responses to climate risks. Multiple factors, such as climate change, including extreme weather events, and countries' socioeconomic status, contribute to greater epidemic risk for less prepared countries (10, 69).

Adoption of short-term actions complemented with long-term responses is often a critical component in surveillance systems under progressive climate risks (46), as exemplified by the management of coffee rust epidemics in Central and South America (9). Long-term plant health requires well-established funding mechanisms balanced across emerging, established, and widespread pathogens (46, 69, 90).

Data governance for biosecurity is an important factor when formulating plant health policy (54, 69, 90). Data governance frameworks need to consider sensitivity about data for personal farm, private, and public interests as well as a balance between data openness (as it allows interoperability and multipurpose reuse) and privacy (as it prevents potential social and economic damage or loss of profit) (90). Data governance should also consider basic FAIR (findability, accessibility, interoperability, and reusability) principles of data stewardship (19).

Rural agricultural regions particularly need to overcome traditional challenges to succeed in a complex, dynamic, and changing environment, and to attain benefits from new technologies. Access to information and communication technologies needed to participate in data collection and modeling or obtain remote advice is limited for smallholder farmers in rural areas; language barriers also need to be overcome to effectively translate disease surveillance and discovery platforms, as exemplified in the Program for Monitoring Emerging Infectious Diseases and the Global Public Health Intelligence Network (88).

RECOMMENDATIONS AND CAPACITY BUILDING

Adapting plant disease management to global change is an ongoing challenge. No-regrets adaptation strategies can focus on improving systems so that they are prepared for both expected and unexpected global change. Improved AI applications in plant pathology can be an important component of better systems, integrating data sets that are both big and high quality using effective machine learning operations. AI incorporates long-proven tools like regression analysis as well as tools whose applications are still expanding, such as image analysis using data from drones or satellites, where we are still discovering what applications are economically viable in which contexts. The development of understandable AI can support public buy-in and greater potential for mechanistic understanding to support the adjustment of models to climate scenarios for which few data are available.

The One CGIAR Plant Health Initiative (PHI) is working to develop a robust disease surveillance system that incorporates reflexive learning, consideration of user needs, and aspirational technology development and deployment. Through this PHI, national and regional phytosanitary institutions in low- and middle-income countries (LMICs) in Africa, Asia, and Latin America will be connected to global surveillance and diagnostic networks, allowing them to exchange knowledge and manage established institutions and emerging plant health threats. The goal is for institutions in LMICs to be better informed about emerging threats and prepared to efficiently respond to pests and diseases exacerbated by changing climatic conditions, international trade, and cropping practices. Groups like One CGIAR may also play a role as brokers for harnessing and disseminating data streams across diverse sources and institutions. Efforts are underway to bring together most of the digital surveillance tools used throughout the CGIAR (81). Promoting the use at the farm level of this anticipated platform of applications will require a diverse set of innovative partnerships with both public and private sectors.

Volatiles: chemicals that are readily vaporized, where volatiles associated with plants may indicate whether they have a disease

Cost of information: the cost of acquiring information for decision-making

Synergies can be developed across projects in plant health by developing a shared AI toolbox, building collaborative systems for data collection, machine learning, and science translation for important pathosystems. An AI toolbox would include tools supporting the plant pathology value chain in general (**Figure 2**). Models and tools to support surveillance and mitigation of global plant disease would generate action prioritization maps (**Figure 1**) based on maps of (*a*) disease presence and ideally severity, (*b*) plant host density and, ideally, resistance gene deployment, (*c*) observed and anticipated future climate variables and, ideally, fine-resolution weather variables, (*d*) remote sensing data, (*e*) trade networks, and (*f*) management practices and their effectiveness. Other key data would include libraries of images and volatiles corresponding to diseased and healthy plants, ideally at scales from individual plants to regions, collected with corresponding information about genotype, date, and location for integration with maps. Models would regularly be used to evaluate the value and cost of information (23), for both fundamental and use-inspired research (144), to prioritize new data collection. Models in the toolbox would address (*a*) weather-based disease risk, (*b*) pathogen-dispersal gradients, and (*c*) disease status predicted from images and volatiles, integrated into (*d*) DSSs for decision-makers at scales from individual farmers to policy makers and regional plant protection organizations. To translate these data and models for managers and to collect useful data and system feedbacks, it will be important to design dashboards and apps that allow users to select the level of detail with which they would like to engage. Translation for policy makers may include analysis of worst-case scenarios, including future invasions in new regions, and recovery plans.

Making this a global toolbox addressing new plant disease challenges is a key component of a global surveillance system (27) and global mitigation system. A global system would build on strengthening national programs and agreements for privacy and defined data sharing. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a good example of potential cooperation across large modeling teams (123). Communities studying individual plant pathosystems rarely include as many scientists as the crop modeling communities in AgMIP, so there are additional incentives for cooperation to make the most of available resources. Globally, NPPOs run the gamut from a handful of people to major endeavors with substantial research teams. The data generated by NPPOs may be "data lakes" that lack the structure for integration into larger systems and models, with data in the form of notes on paper or in spreadsheets with differing formats and metadata. Capacity building is central to building a global system. As AI–human interfaces improve, there may be interesting possibilities for designing training that is matched to specific pathosystems and the needs of specific countries and NPPOs.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

We appreciate the support of the CGIAR Research Program on Roots, Tubers and Bananas (RTB), supported by CGIAR Trust Fund contributors (**https://www.cgiar.org/funders/**); USDA APHIS agreements 11-8453-1483-CA and AP21PPQS&T00C195; USDA NIFA grants 2015-51181-24257 and 2020-51181-32198; Foundation for Food and Agriculture Research Grant FF-NIA19-0000000050; NASA ROSES grants 80NSSC20K1533 and 80NSSC21K1605; the Keck Foundation; University of Florida; and Cornell University. This paper may not necessarily reflect the views of these organizations.

LITERATURE CITED

1. Adadi A, Berrada M. 2018. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access* 6:52138–60
2. Andersen KF, Buddenhagen CE, Rachkara P, Gibson R, Kalule S, et al. 2019. Modeling epidemics in seed systems and landscapes to guide management strategies: the case of sweet potato in Northern Uganda. *Phytopathology* 109:1519–32
3. Andersen Onofre KF, Forbes GA, Andrade-Piedra JL, Buddenhagen CE, Fulton J, et al. 2021. An integrated seed health strategy and phytosanitary risk assessment: potato in the Republic of Georgia. *Agric. Syst.* 191:103144
4. Anderson W, You L, Wood S, Wood-Sichra U, Wu W. 2015. An analysis of methodological and spatial differences in global cropping systems models and maps. *Glob. Ecol. Biogeogr.* 24:180–91
5. Andrade-Piedra JL, Forbes GA, Shtienberg D, Grunwald NJ, Chacon MG, et al. 2005. Qualification of a plant disease simulation model: performance of the LATEBLIGHT model across a broad range of environments. *Phytopathology* 95:1412–22
6. Andrade-Piedra JL, Hijmans RJ, Forbes GA, Fry WE, Nelson RJ. 2005. Simulation of potato late blight in the Andes. I: Modification and parameterization of the LATEBLIGHT model. *Phytopathology* 95:1191–99
7. Andrade-Piedra JL, Hijmans RJ, Juarez HS, Forbes GA, Shtienberg D, Fry WE. 2005. Simulation of potato late blight in the Andes. II: Validation of the LATEBLIGHT model. *Phytopathology* 95:1200–8
8. Atzori L, Iera A, Morabito G. 2010. The internet of things: a survey. *Comput. Netw.* 54:2787–805
9. Avelino J, Cristancho M, Georgiou S, Imbach P, Aguilar L, et al. 2015. The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. *Food Secur.* 7:303–21
10. Baker RE, Mahmud AS, Miller IF, Rajeev M, Rasambainarivo F, et al. 2021. Infectious disease in an era of global change. *Nat. Rev. Microbiol.* 20:193–205
11. Bates S, Hastie T, Tibshirani R. 2021. Cross-validation: What does it estimate and how well does it do it? arXiv:2104.00673 [stat.ME]
12. Bauer P, Stevens B, Hazeleger W. 2021. A digital twin of Earth for the green transition. *Nat. Clim. Change* 11:80–83
13. Bebber DP. 2015. Range-expanding pests and pathogens in a warming world. *Annu. Rev. Phytopathol.* 53:335–56
14. Benami E, Jin Z, Carter MR, Ghosh A, Hijmans RJ, et al. 2021. Uniting remote sensing, crop modelling and economics for agricultural risk management. *Nat. Rev. Earth Environ.* 2:140–59
15. Bernard F, Sache I, Suffert F, Chelle M. 2013. The development of a foliar fungal pathogen does react to leaf temperature! *New Phytol.* 198:232–40
16. Bhattacharya B, Chattopadhyay C. 2013. A multi-stage tracking for mustard rot disease combining surface meteorology and satellite remote sensing. *Comput. Electron. Agric.* 90:35–44
17. Blandon-Diaz JU, Forbes GA, Andrade-Piedra JL, Yuen JE. 2011. Assessing the adequacy of the simulation model LATEBLIGHT under Nicaraguan conditions. *Plant Dis.* 95:839–46
18. Bock CH, Barbedo JG, Del Ponte EM, Bohnenkamp D, Mahlein A-K. 2020. From visual estimates to fully automated sensor-based measurements of plant disease severity: status and challenges for improving accuracy. *Phytopathol. Res.* 2:9

19. Boeckhout M, Zielhuis GA, Bredenoord AL. 2018. The FAIR guiding principles for data stewardship: fair enough? *Eur. J. Hum. Genet.* 26:931–36
20. Bohnenkamp D, Behmann J, Mahlein A-K. 2019. In-field detection of yellow rust in wheat on the ground canopy and UAV scale. *Remote Sens*. 11:2495
21. Bohnenkamp D, Behmann J, Paulus S, Steiner U, Mahlein A-K. 2021. A hyperspectral library of foliar diseases of wheat. *Phytopathology* 111:1583–93
22. Buddenhagen CE, Hernandez Nopsa JF, Andersen KF, Andrade-Piedra J, Forbes GA, et al. 2017. Epidemic network analysis for mitigation of invasive pathogens in seed systems: potato in Ecuador. *Phytopathology* 107:1209–18
23. Buddenhagen CE, Xing Y, Andrade Piedra JL, Forbes GA, Kromann P, et al. 2022. Where to invest project efforts for greater benefit: a framework for management performance mapping with examples for potato seed health. *Phytopathology* 112:1431–43
24. Bütikofer L, Anderson K, Bebber DP, Bennie JJ, Early RI, Maclean IM. 2020. The problem of scale in predicting biological responses to climate. *Glob. Change Biol.* 26:6657–66
25. Bzdok D, Altman N, Krzywinski M. 2018. Statistics versus machine learning. *Nat. Methods* 15:233–34
26. Camino C, Calderón R, Parnell S, Dierkes H, Chemin Y, et al. 2021. Detection of *Xylella fastidiosa* in almond orchards by synergic use of an epidemic spread model and remotely sensed plant traits. *Remote Sens. Environ*. 260:112420
27. Carvajal-Yepes M, Cardwell K, Nelson A, Garrett KA, Giovani B, et al. 2019. A global surveillance system for crop diseases. *Science* 364:1237–39
28. Chaloner TM, Gurr SJ, Bebber DP. 2020. Geometry and evolution of the ecological niche in plant-associated microbes. *Nat. Commun.* 11:2955
29. Chaloner TM, Gurr SJ, Bebber DP. 2021. Plant pathogen infection risk tracks global crop yields under climate change. *Nat. Climate Change* 11:710–15
30. Chapman D, Purse BV, Roy HE, Bullock JM. 2017. Global trade networks determine the distribution of invasive non-native species. *Glob. Ecol. Biogeogr.* 26:907–17
31. Chen QL, Hu HW, Yan ZZ, Li CY, Nguyen BAT, et al. 2021. Precipitation increases the abundance of fungal plant pathogens in Eucalyptus phyllosphere. *Environ. Microbiol.* 23:7688–700
32. Chouhan SS, Singh UP, Jain S. 2020. Applications of computer vision in plant pathology: a survey. *Arch. Comput. Methods Eng.* 27:611–32
33. Clohessy JW, Sanjel S, O'Brien GK, Barocco R, Kumar S, et al. 2021. Development of a high-throughput plant disease symptom severity assessment tool using machine learning image analysis and integrated geolocation. *Comput. Electron. Agric.* 184:106089
34. Coakley SM, Scherm H, Chakraborty S. 1999. Climate change and plant disease management. *Annu. Rev. Phytopathol.* 37:399–426
35. Cotrozzi L, Couture JJ. 2020. Hyperspectral assessment of plant responses to multi-stress environments: prospects for managing protected agrosystems. *Plants People Planet* 2:244–58
36. Couture JJ, Serbin SP, Townsend PA. 2013. Spectroscopic sensitivity of real-time, rapidly induced phytochemical change in response to damage. *New Phytol.* 198:311–19
37. Couture JJ, Singh A, Rubert-Nason KF, Serbin SP, Lindroth RL, Townsend PA. 2016. Spectroscopic determination of ecologically relevant plant secondary metabolites. *Methods Ecol. Evol.* 7:1402–12
38. Cunniffe NJ, Stutt RO, DeSimone RE, Gottwald TR, Gilligan CA. 2015. Optimising and communicating options for the control of invasive plant disease when there is epidemiological uncertainty. *PLOS Comput. Biol.* 11:e1004211
39. Curran PJ. 1989. Remote sensing of foliar chemistry. *Remote Sens. Environ.* 30:271–78
40. Dalla Lana F, Madden LV, Paul PA. 2021. Logistic models derived using LASSO methods for quantifying the risk of natural contamination of maize grain with deoxynivalenol. *Phytopathology* 111:2250–67
41. Delgado C, Benitez H, Cruz M, Selvaraj M. 2019. Digital disease phenotyping. In *Proceedings of the IGARSS 2019—2019 IEEE International Geoscience and Remote Sensing Symposium*, pp. 5702–5. New York: IEEE
42. Delgado-Baquerizo M, Guerra CA, Cano-Díaz C, Egidi E, Wang J-T, et al. 2020. The proportion of soil-borne pathogens increases with warming at the global scale. *Nat. Clim. Change* 10:550–54

43. DeWolf ED, Francl LJ. 1997. Neural networks that distinguish infection periods of wheat tan spot in an outdoor environment. *Phytopathology* 87:83–87
44. Dormann CF, Schymanski SJ, Cabral J, Chuine I, Graham C, et al. 2012. Correlation and process in species distribution models: bridging a dichotomy. *J. Biogeogr.* 39:2119–31
45. Dossa GS, Sparks A, Cruz CV, Oliva R. 2015. Decision tools for bacterial blight resistance gene deployment in rice-based agricultural ecosystems. *Front. Plant Sci.* 6:305
46. Drenth A, Kema G. 2021. The vulnerability of bananas to globally emerging disease threats. *Phytopathology* 111:2146–61
47. Duarte-Carvajalino JM, Alzate DF, Ramirez AA, Santa-Sepulveda JD, Fajardo-Rojas AE, Soto-Suárez M. 2018. Evaluating late blight severity in potato crops using unmanned aerial vehicles and machine learning algorithms. *Remote Sens.* 10:1513
48. Dudney J, Willing CE, Das AJ, Latimer AM, Nesmith JC, Battles JJ. 2021. Nonlinear shifts in infectious rust disease due to climate change. *Nat. Commun.* 12:5102
49. Dutta S, Singh SK, Khullar M. 2014. A case study on forewarning of yellow rust affected areas on wheat crop using satellite data. *J. Indian Soc. Remote Sens.* 42:335–42
50. Early R, Bradley BA, Dukes JS, Lawler JJ, Olden JD, et al. 2016. Global threats from invasive alien species in the twenty-first century and national response capacities. *Nat. Commun.* 7:12485
51. Efron B. 2020. Prediction, estimation, and attribution. *Int. Stat. Rev.* 88:S28–S59
52. Eitzinger A, Binder CR, Meyer MA. 2018. Risk perception and decision-making: Do farmers consider risks from climate change? *Clim. Change* 151:507–24
53. Erickson B, Fausti SW. 2021. The role of precision agriculture in food security. *Agron. J.* 113:4455–62
54. Evans SW, Beal J, Berger K, Bleijs DA, Cagnetti A, et al. 2020. Embrace experimentation in biosecurity governance. *Science* 368:138–40
55. Fenu G, Malloci FM. 2021. Forecasting plant and crop disease: an explorative study on current algorithms. *Big Data Cogn. Comput.* 5:2
56. Fones HN, Bebber DP, Chaloner TM, Kay WT, Steinberg G, Gurr SJ. 2020. Threats to global food security from emerging fungal and oomycete crop pathogens. *Nat. Food* 1:332–42
57. Gao B-C. 1996. NDWI: a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* 58:257–66
58. Garcia-Figuera S, Grafton-Cardwell EE, Babcock BA, Lubell MN, McRoberts N. 2021. Institutional approaches for plant health provision as a collective action problem. *Food Secur.* 13:273–90
59. Garrett KA. 2021. Impact network analysis and the INA R package: decision support for regional management interventions. *Methods Ecol. Evol.* 12:1634–47
60. Garrett KA, Alcalá-Briseño RI, Andersen KF, Brawner J, Choudhury RA, et al. 2020. Effective altruism as an ethical lens on research priorities. *Phytopathology* 110:708–22
61. Garrett KA, Alcalá-Briseño RI, Andersen KF, Choudhury RA, Dantes W, et al. 2020. Adapting disease management systems under global change. In *Emerging Plant Diseases and Global Food Security*, ed. J Ristaino, A Records, pp. 31–50. St. Paul, MN: APS Press
62. 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
63. Garrett KA, Forbes GA, Savary S, Skelsey P, Sparks AH, et al. 2011. Complexity in climate-change impacts: an analytical framework for effects mediated by plant disease. *Plant Pathol.* 60:15–30
64. Gillon D, Houssard C, Joffre R. 1999. Using near-infrared reflectance spectroscopy to predict carbon, nitrogen and phosphorus content in heterogeneous plant material. *Oecologia* 118:173–82
65. Gold KM. 2021. Plant disease sensing: studying plant-pathogen interactions at scale. *mSystems* 6:e01228-21
66. Gold KM, Townsend PA, Herrmann I, Gevens AJ. 2020. Investigating potato late blight physiological differences across potato cultivars with spectroscopy and machine learning. *Plant Sci.* 295:110316
67. Griffel L, Delparte D, Edwards J. 2018. Using Support Vector Machines classification to differentiate spectral signatures of potato plants infected with Potato virus Y. *Comput. Electron. Agric.* 153:318–24
68. Gunning D, Stefik M, Choi J, Miller T, Stumpf S, Yang G-Z. 2019. XAI—explainable artificial intelligence. *Sci. Robot.* 4:aay7120

69. Halliday FEB, Hampson K, Hanley N, Lembo T, Sharp JP, et al. 2017. Driving improvements in emerging disease surveillance through locally relevant capacity strengthening. *Science* 357:146–48
70. Heim RH, Carnegie AJ, Zarco-Tejada PJ. 2019. Breaking down barriers between remote sensing and plant pathology. *Trop. Plant Pathol.* 44:398–400
71. Herrmann I, Vosberg SK, Ravindran P, Singh A, Chang H-X, et al. 2018. Leaf and canopy level detection of *Fusarium virguliforme* (sudden death syndrome) in soybean. *Remote Sens*. 10:426
72. Hofman JM, Watts DJ, Athey S, Garip F, Griffiths TL, et al. 2021. Integrating explanation and prediction in computational social science. *Nature* 595:181–88
73. IPCC. 2013. Climate change 2013: the physical science basis. In *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. TF Stocker, D Qin, G-K Plattner, M Tignor, SK Allen, et al. Cambridge, UK: Cambridge Univ. Press
74. Ireland KB, Hardy GE, Kriticos DJ. 2013. Combining inferential and deductive approaches to estimate the potential geographical range of the invasive plant pathogen, *Phytophthora ramorum*. *PLOS ONE* 8:e63508
75. Jackson RD. 1986. Remote sensing of biotic and abiotic plant stress. *Annu. Rev. Phytopathol.* 24:265–87
76. Jeger MJ, Pautasso M. 2008. Plant disease and global change: the importance of long-term data sets. *New Phytol*. 177:8–11
77. Jones RAC, Barbetti MJ. 2012. Influence of climate change on plant disease infections and epidemics caused by viruses and bacteria. *CAB Rev*. 7:1–33
78. Juroszek P, Racca P, Link S, Farhumand J, Kleinhenz B. 2020. Overview on the review articles published during the past 30 years relating to the potential climate change effects on plant pathogens and crop disease risks. *Plant Pathol.* 69:179–93
79. Kamilaris A, Prenafeta-Boldú FX. 2018. Deep learning in agriculture: a survey. *Comput. Electron. Agric.* 147:70–90
80. Kokaly RF, Skidmore AK. 2015. Plant phenolics and absorption features in vegetation reflectance spectra near 1.66 μm. *Int. J. Appl. Earth Obs. Geoinf.* 43:55–83
81. Kreuze J, Adewopo J, Selvaraj M, Mwanzia L, Lava Kumar P, et al. 2022. Innovative digital technologies to monitor and control pest and disease threats in root, tuber, and banana (RT&B) cropping systems: progress and prospects. In *Root, Tuber and Banana Food System Innovations*, ed. G Thiele, M Friedmann, H Campos, V Polar, JW Bentley, pp. 261–88. Cham, Switz.: Springer
82. Launay M, Zurfluh O, Huard F, Buis S, Bourgeois G, et al. 2020. Robustness of crop disease response to climate change signal under modeling uncertainties. *Agric. Syst.* 178:102733
83. Lazer D, Kennedy R, King G, Vespignani A. 2014. The parable of Google Flu: traps in big data analysis. *Science* 343:1203–5
84. Lewis CM, Persoons A, Bebber DP, Kigathi RN, Maintz J, et al. 2018. Potential for re-emergence of wheat stem rust in the United Kingdom. *Commun. Biol.* 1:13
85. Li Z, Paul R, Tis TB, Saville AC, Hansel JC, et al. 2019. Non-invasive plant disease diagnostics enabled by smartphone-based fingerprinting of leaf volatiles. *Nat. Plants* 5:856–66
86. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. 2018. Machine learning in agriculture: a review. *Sensors* 18:2674
87. Linardatos P, Papastefanopoulos V, Kotsiantis S. 2021. Explainable AI: a review of machine learning interpretability methods. *Entropy* 23:18
88. Lipkin WI. 2013. The changing face of pathogen discovery and surveillance. *Nat. Rev. Microbiol.* 11:133–41
89. Liu E, Gold KM, Combs D, Cadle-Davidson L, Jiang Y. 2021. Deep learning-based autonomous downy mildew detection and severity estimation in vineyards. In *Proceedings of the 2021 ASABE Annual International Virtual Meeting*. St. Joseph, MI: Am. Soc. Agric. Biol. Eng.
90. Magarey RD, Colunga-Garcia M, Fieselmann DA. 2009. Plant biosecurity in the United States: roles, responsibilities, and information needs. *BioScience* 59:875–84
91. Mahlein A-K. 2016. Plant disease detection by imaging sensors: parallels and specific demands for precision agriculture and plant phenotyping. *Plant Dis*. 100:241–51
92. Mahlein A-K, Kuska MT, Behmann J, Polder G, Walter A. 2018. Hyperspectral sensors and imaging technologies in phytopathology: state of the art. *Annu. Rev. Phytopathol.* 56:535–58

93. Mahlein A-K, Kuska MT, Thomas S, Wahabzada M, Behmann J, et al. 2019. Quantitative and qualitative phenotyping of disease resistance of crops by hyperspectral sensors: seamless interlocking of phytopathology, sensors, and machine learning is needed! *Curr. Opin. Plant Biol.* 50:156–62
94. Mañez M, Carmona M, Haro D, Hanger S. 2016. Risk perception. In *Novel Multi-Sector Partnerships in Disaster Risk Management*: *Results of the ENHANCE Project*, ed. J Aerts, J Mysiak, pp. 51–67. Brussels: Proj. ENHANCE
95. Marcus G. 2018. Deep learning: a critical appraisal. arXiv:1801.00631 [cs.AI]
96. Martinetti D, Soubeyrand S. 2019. Identifying lookouts for epidemio-surveillance: application to the emergence of *Xylella fastidiosa* in France. *Phytopathology* 109:265–76
97. Meyer M, Cox JA, Hitchings MDT, Burgin L, Hort MC, et al. 2017. Quantifying airborne dispersal routes of pathogens over continents to safeguard global wheat supply. *Nat. Plants* 3:780–86
98. Mirik M, Jones D, Price J, Workneh F, Ansley R, Rush C. 2011. Satellite remote sensing of wheat infected by wheat streak mosaic virus. *Plant Dis.* 95:4–12
99. Mohanty SP, Hughes DP, Salathé M. 2016. Using deep learning for image-based plant disease detection. *Front. Plant Sci.* 7:1419
100. Mooney SJ, Pejaver V. 2018. Big data in public health: terminology, machine learning, and privacy. *Annu. Rev. Public Health* 39:95–112
101. Mrisho LM, Mbilinyi NA, Ndalahwa M, Ramcharan AM, Kehs AK, et al. 2020. Accuracy of a smartphone-based object detection model, PlantVillage Nuru, in identifying the foliar symptoms of the viral diseases of cassava: CMD and CBSD. *Front. Plant Sci.* 11:590889
102. Nagarajan S, Seibold G, Kranza J, Saari E, Joshi L. 1984. Monitoring wheat rust epidemics with the Landsat-2 satellite. *Phytopathology* 74:585–87
103. Narouei-Khandan HA, Shakya SK, Garrett KA, Goss EM, Dufault NS, et al. 2020. BLIGHTSIM: A new potato late blight model simulating the response of phytophthora infestans to diurnal temperature and humidity fluctuations in relation to climate change. *Pathogens* 9:659
104. Naudé W. 2020. Artificial intelligence versus COVID-19: limitations, constraints and pitfalls. *AI Soc.* 35:761–65
105. Newlands NK. 2018. Model-based forecasting of agricultural crop disease risk at the regional scale, integrating airborne inoculum, environmental, and satellite-based monitoring data. *Front. Environ. Sci.* 6:63
106. Nieke J, Rast M. 2018. Towards the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME). In *Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium*, pp. 157–59. New York: IEEE
107. Nilsson HE. 1969. Studies of root and foot rot diseases of cereals and grasses. I. On resistance to *Ophiobolus graminis* Sacc. *Lantbr. Ann.* 35:275–807
108. Oberti R, Marchi M, Tirelli P, Calcante A, Iriti M, et al. 2016. Selective spraying of grapevines for disease control using a modular agricultural robot. *Biosyst. Eng.* 146:203–15
109. Ocimati W, Bouwmeester H, Groot JC, Tittonell P, Brown D, Blomme G. 2019. The risk posed by Xanthomonas wilt disease of banana: mapping of disease hotspots, fronts and vulnerable landscapes. *PLOS ONE* 14:e0213691
110. Oerke E-C. 2020. Remote sensing of diseases. *Annu. Rev. Phytopathol.* 58:225–52
111. Onofre RB, Gadoury DM, Stensvand A, Bierma A, Rea MS, Peres NA. 2021. Use of ultraviolet light to suppress powdery mildew in strawberry fruit production fields. *Plant Dis.* 105:2402–9
112. Oren R, Schulze E-D, Matyssek R, Zimmermann R. 1986. Estimating photosynthetic rate and annual carbon gain in conifers from specific leaf weight and leaf biomass. *Oecologia* 70:187–93
113. Parnell S, Gottwald TR, Gilligan CA, Cunniffe NJ, van den Bosch F. 2010. The effect of landscape pattern on the optimal eradication zone of an invading epidemic. *Phytopathology* 100:638–44
114. Parnell S, van den Bosch F, Gottwald T, Gilligan CA. 2017. Surveillance to inform control of emerging plant diseases: an epidemiological perspective. *Annu. Rev. Phytopathol.* 55:591–610
115. Pautasso M, Doring TF, Garbelotto M, Pellis L, Jeger MJ. 2012. Impacts of climate change on plant disease—opinions and trends. *Eur. J. Plant Pathol.* 133:295–313
116. Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modeling of species geographic distributions. *Ecol. Model.* 190:231–59

117. Polder G, Blok PM, De Villiers HA, Van der Wolf JM, Kamp J. 2019. Potato virus Y detection in seed potatoes using deep learning on hyperspectral images. *Front. Plant Sci.* 10:209
118. Poudel R, Jumpponen A, Schlatter DC, Paulitz TC, McSpadden Gardener B, et al. 2016. Microbiome networks: a systems framework for identifying candidate microbial assemblages for disease management. *Phytopathology* 106:1083–96
119. Prank M, Kenaley SC, Bergstrom GC, Acevedo M, Mahowald NM. 2019. Climate change impacts the spread potential of wheat stem rust, a significant crop disease. *Environ. Res. Lett.* 14:124053
120. Prosperi M, Min JS, Bian J, Modave F. 2018. Big data hurdles in precision medicine and precision public health. *BMC Med. Inf. Decis. Mak.* 18:139

120a. Ramcharan A, Baranowski K, McCloskey P, Ahmed B, Legg J, Hughes DP. 2017. Deep learning for image-based cassava disease detection. *Front. Plant Sci*. 8:1852

121. Ristaino JB, Anderson PK, Bebber DP, Brauman KAC, Cunniffe NJ, et al. 2021. The persistent threat of emerging plant disease pandemics to global food security. *PNAS* 118:e20222239118
122. Rosenzweig C, Iglesias A, Yang XB, Epstein PR, Chivian E. 2001. Climate change and extreme weather events: implications for food production, plant diseases, and pests. *Glob. Change Hum. Health* 2:90–104
123. Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, et al. 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): protocols and pilot studies. *Agric. For. Meteorol.* 170:166–82
124. Rosenzweig C, Ruane AC, Antle J, Elliott J, Ashfaq M, et al. 2018. Coordinating AgMIP data and models across global and regional scales for 1.5 C and 2.0 C assessments. *Philos. Trans. R. Soc. A* 376:20160455
125. Samek W, Müller K-R. 2019. Towards explainable artificial intelligence. In *Explainable AI*: *Interpreting*, *Explaining and Visualizing Deep Learning*, ed. W Samek, G Montavon, A Vedaldi, LK Hansen, KR Müller, pp. 5–22. New York: Springer
126. Savary S, Willocquet L, Pethybridge SJ, Esker P, McRoberts N, Nelson A. 2019. The global burden of pathogens and pests on major food crops. *Nat. Ecol. Evol.* 3:430–39
127. Scherm H, Thomas CS, Garrett KA, Olsen JM. 2014. Meta-analysis and other approaches for synthesizing structured and unstructured data in plant pathology. *Annu. Rev. Phytopathol.* 52:453–76
128. Schmale DG III, Ross SD. 2015. Highways in the sky: scales of atmospheric transport of plant pathogens. *Annu. Rev. Phytopathol.* 53:591–611
129. Schneider F, Ferraz A, Schimel D. 2019. Watching Earth's interconnected systems at work. *Eos*. **https://eos.org/science-updates/watching-earths-interconnected-systems-at-work**
130. Schramowski P, Stammer W, Teso S, Brugger A, Herbert F, et al. 2020. Making deep neural networks right for the right scientific reasons by interacting with their explanations. *Nat. Mach. Intell.* 2:476–86
131. Schultz M, Betancourt C, Gong B, Kleinert F, Langguth M, et al. 2021. Can deep learning beat numerical weather prediction? *Philos. Trans. R. Soc. A* 379:20200097
132. Selvaraj MG, Vergara A, Montenegro F, Ruiz HA, Safari N, et al. 2020. Detection of banana plants and their major diseases through aerial images and machine learning methods: a case study in DR Congo and Republic of Benin. *ISPRS J. Photogr. Remote Sens.* 169:110–24
133. Selvaraj MG, Vergara A, Ruiz H, Safari N, Elayabalan S, et al. 2019. AI-powered banana diseases and pest detection. *Plant Methods* 15:92
134. Serbin SP, Wu J, Ely KS, Kruger EL, Townsend PA, et al. 2019. From the Arctic to the tropics: multibiome prediction of leaf mass per area using leaf reflectance. *New Phytol*. 224:1557–68
135. Shah D, Paul P, De Wolf E, Madden L. 2019. Predicting plant disease epidemics from functionally represented weather series. *Philos. Trans. R. Soc. B* 374:20180273
136. Shakoor N, Lee S, Mockler TC. 2017. High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field. *Curr. Opin. Plant Biol.* 38:184–92
137. Sidey-Gibbons JA, Sidey-Gibbons CJ. 2019. Machine learning in medicine: a practical introduction. *BMC Med. Res. Methodol.* 19:64
138. Singh A, Serbin SP, McNeil BE, Kingdon CC, Townsend PA. 2015. Imaging spectroscopy algorithms for mapping canopy foliar chemical and morphological traits and their uncertainties. *Ecol. Appl.* 25:2180–97
139. Skelsey P. 2021. Forecasting risk of crop disease with anomaly detection algorithms. *Phytopathology* 111:321–32

140. Small IM, Joseph L, Fry WE. 2015. Development and implementation of the BlightPro decision support system for potato and tomato late blight management. *Comput. Electron. Agric.* 115:57–65
141. Soberón J, Peterson AT. 2005. Interpretation of models of fundamental ecological niches and species' distributional areas. *Biodivers. Inf.* **http://doi.org/10.17161/bi.v2i0.4**
142. Sousa D, Fisher JB, Galvan FR, Pavlick RP, Cordell S, et al. 2021. Tree canopies reflect mycorrhizal composition. *Geophys. Res. Lett.* 48:e2021GL092764
143. Sparks AH, Forbes GA, Hijmans RJ, Garrett KA. 2014. Climate change may have limited effect on the global risk of potato late blight. *Glob. Change Biol.* 20:3621–31
144. Stokes DE. 1997. *Pasteur's Quadrant: Basic Science and Technological Innovation*. Washington, DC: Brookings
145. Suthaparan A, Solhaug K, Bjugstad N, Gislerød H, Gadoury D, Stensvand A. 2016. Suppression of powdery mildews by UV-B: application frequency and timing, dose, reflectance, and automation. *Plant Dis.* 100:1643–50
146. Topçuoğlu BD, Lesniak NA, Ruffin MT IV, Wiens J, Schloss PD. 2020. A framework for effective application of machine learning to microbiome-based classification problems. *mBio* 11:e00434-20
147. Trolley G, Romero F, Pavlick R, Starr C, Gold K. 2021. *Grapevine variety discrimination using airborne hyperspectral imagery*. Paper presented at the 2021 AGU Fall Meeting, Chicago
148. Tzounis A, Katsoulas N, Bartzanas T, Kittas C. 2017. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* 164:31–48
149. Varshney RK, Singh VK, Hickey JM, Xun X, Marshall DF, et al. 2016. Analytical and decision support tools for genomics-assisted breeding. *Trends Plant Sci.* 21:354–63
150. Venette RC, Cohen SD. 2006. Potential climatic suitability for establishment of *Phytophthora ramorum* within the contiguous United States. *For. Ecol. Manag.* 231:18–26
151. Větrovský T, Kohout P, Kopecký M, Machac A, Man M, et al. 2019. A meta-analysis of global fungal distribution reveals climate-driven patterns. *Nat. Commun.* 10:5142
152. Wang C, Wang X, Jin Z, Müller C, Pugh TA, et al. 2021. Occurrence of crop pests and diseases has largely increased in China since 1970. *Nat. Food* 3:57–65
153. Wang Z, Chlus A, Geygan R, Ye Z, Zheng T, et al. 2020. Foliar functional traits from imaging spectroscopy across biomes in eastern North America. *New Phytol.* 228:494–511
154. Wang Z, Townsend PA, Schweiger AK, Couture JJ, Singh A, et al. 2019. Mapping foliar functional traits and their uncertainties across three years in a grassland experiment. *Remote Sens. Environ.* 221:405–16
155. Wood JR, Díaz FP, Latorre C, Wilmshurst JM, Burge OR, Gutiérrez RA. 2018. Plant pathogen responses to Late Pleistocene and Holocene climate change in the central Atacama Desert, Chile. *Sci. Rep.* 8:17208
156. Xing Y, Hernandez Nopsa JF, Andersen KF, Andrade-Piedra JL, Beed FD, et al. 2020. Global cropland connectivity: a risk factor for invasion and saturation by emerging pathogens and pests. *BioScience* 70:744–58
157. Yuan M, Couture JJ, Townsend PA, Ruark MD, Bland WL. 2016. Spectroscopic determination of leaf nitrogen concentration and mass per area in sweet corn and snap bean. *Agron. J.* 108:2519–26
158. Zarco-Tejada P, Poblete T, Camino C, Gonzalez-Dugo V, Calderon R, et al. 2021. Divergent abiotic spectral pathways unravel pathogen stress signals across species. *Nat. Commun.* 12:6088
159. Zhai Y, Cui L, Zhou X, Gao Y, Fei T, Gao W. 2013. Estimation of nitrogen, phosphorus, and potassium contents in the leaves of different plants using laboratory-based visible and near-infrared reflectance spectroscopy: comparison of partial least-square regression and support vector machine regression methods. *Int. J. Remote Sens.* 34:2502–18
160. Zhang M, Qin Z, Liu X. 2005. Remote sensed spectral imagery to detect late blight in field tomatoes. *Precis. Agric.* 6:489–508