The Use and Role of Predictive Systems in Disease Management

David H. Gent,[1,3,*] Walter F. Mahaffee,[2,3] Neil McRoberts,[4] and William F. Pfender[1,3]

[1]U.S. Department of Agriculture-Agricultural Research Service, Forage Seed and Cereal Research Unit, Corvallis, Oregon 97331; email: dave.gent@ars.usda.gov, bill.pfender@ars.usda.gov

[2]U.S. Department of Agriculture-Agricultural Research Service, Horticultural Crops Research Unit, Corvallis, Oregon 97330; email: walt.mahaffee@ars.usda.gov

[3]Department of Botany and Plant Pathology, Oregon State University, Corvallis, Oregon 97330

[4]Plant Pathology Department, University of California, Davis, California, 95616-8751; email: nmcroberts@ucdavis.edu

Annu. Rev. Phytopathol. 2013. 51:267–89

First published online as a Review in Advance on May 13, 2013

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

This article's doi:
doi: 10.1146/annurev-phyto-082712-102356

*Corresponding author

Keywords

diffusion theory, disease control, disease forecasting, IPM adoption, plant pathogen

Abstract

Disease predictive systems are intended to be management aids. With a few exceptions, these systems typically do not have direct sustained use by growers. Rather, their impact is mostly pedagogic and indirect, improving recommendations from farm advisers and shaping management concepts. The degree to which a system is consulted depends on the amount of perceived new, actionable information that is consistent with the objectives of the user. Often this involves avoiding risks associated with costly disease outbreaks. Adoption is sensitive to the correspondence between the information a system delivers and the information needed to manage a particular pathosystem at an acceptable financial risk; details of the approach used to predict disease risk are less important. The continuing challenge for researchers is to construct tools relevant to farmers and their advisers that improve upon their current management skill. This goal requires an appreciation of growers' decision calculus in managing disease problems and, more broadly, their overall farm enterprise management.

INTRODUCTION

Risk: uncertainty that can be estimated by measuring key outcomes over time and summarizing data as a probability distribution

Identification, description, and quantification of the components of a disease cycle are foundational to plant disease epidemiology and efficient disease management. Without this information, management efforts may not be targeted appropriately or efficiently. When there is sufficient understanding of how biological and environmental factors interact to drive disease outbreaks and crop damage, predictions of system behavior and of need for intervention can be made with some hope of success. Predicting conditions that warrant intervention is considered a key tenet of the concept of integrated pest management (IPM) (102), with some authors proposing that use of expert systems and dynamic crop-pest models are characteristics of higher-level IPM (42, 48). The basic premise for developing predictive systems, then, seems rational and persuasive: produce a tangible product that provides decision makers with accessible and useful science-based information to make better decisions. Objective demonstration of fitness for purpose is expected to drive demand (hence adoption) and lead to overall improvement in decision making across an adopting population.

This review assesses the degree to which this premise has been supported in practice. It focuses on the recurring themes of how predictive systems tend to be used and on the characteristics of pathosystems and predictive systems where their use has been sustained. The long history of development of predictive systems in plant pathology, and in the broader agricultural sciences, is used to explore when, where, and how predictive systems have been applied. We point out that persistent deficiencies in the evaluation process impede full assessment of the contribution of predictive systems to plant disease management. Numerous reviews that summarize development and implementation of predictive systems, models, and decision support tools provide scaffolding for this paper (7, 8, 10, 16, 20, 33, 44, 65, 66, 74, 93, 96).

Some qualifications of this review are needed at the outset. Assessing the degree to which predictive systems are used in disease control is an immense task given the number and diversity of predictive systems, the fuzzy definition of "use," and the typically poor documentation of their impact. Adoption is a more complex process than a single dichotomous event, and what counts as ongoing use of predictive systems is nuanced. This review is not intended to be an exhaustive presentation of all evidence or viewpoints. Omissions of both fact and opinion are inevitable; readers are encouraged to consider alternative starting points for their own exploration of this topic (e.g., 27, 93, 115, 121).

TERMINOLOGY AND FORMS OF PREDICTIVE SYSTEMS

A menagerie of terms is used to describe predictors of plant disease. Disease predictor, disease forecaster, warning system, pastcaster, disease model, decision aid, decision support system, risk algorithm, risk index, expert system, and predictive system appear in the literature (8, 20, 33, 44, 74, 96) and sometimes are differentiated (e.g., see 59). These differences are not important here, and "predictive system" is used as a general term for formalized algorithms that assess disease risk factors to inform the need for crop protection.

No single optimal design exists for predictive systems, and diverse approaches have been taken in their development (20, 44, 50, 66, 106, 120). Predictive systems range from sampling schemes to rules of thumb (e.g., treat after disease detection but before a forecasted rain event) to simple categorical rules (e.g., treat after co-occurrence of >2.54 mm rain and temperature >10°C) to complex, multicriteria optimization programs based on process submodels. Some predictive systems encompass all phases of a cropping situation, integrating mechanistic simulation models, databases of information, and decision analysis rules to predict possible outcomes or specify management actions. All involve estimation or measurement of some component of the disease cycle, implicitly or explicitly, such as weather, pathogen, host, cultural practices and other crop management actions, and even risk expectations (20).

ASSESSING USE OF DISEASE PREDICTORS IN DISEASE MANAGEMENT

Encapsulation of information in disease predictive systems has long been postulated to lead to progress in disease management by facilitating better-informed decision making (e.g., see 74). Adoption of predictive systems was anticipated as the cost of pesticides and regulatory constraints increased and pesticide registrations decreased (e.g., see 11, 44, 47, 50, 75). Paralleling these predictions is an almost equally large body of opinion, dating back to the initial introductions of predictive systems, that contests that these systems are (or appear to be) underutilized by farmers in practical disease control (e.g., see 11, 44, 47, 60, 113). This problem of implementation is often discussed but poorly documented because of the difficulty and cost associated with collecting data on rates of adoption and retention of use. Even when documented, the criteria for what constitutes utilization seem to be rather limited and unclear (see sidebar, Utility of Predictive Systems).

The general view of limited implementation seems to be inferred from observations that a minority of farmers directly utilize a system, that there is general resistance toward the concept of disease prediction, or that use of the predictive system is not sustained over time (e.g., see 75). Others assert that for a predictive system to be successful it must be adopted and implemented directly by growers (11). We suggest that these criteria fail to encompass the process and informational sources that surround farm management decision making (71). They also hint at neglect by the research community to invest in understanding how these tools are actually used and learned by the clientele being served. Methods for assessing technology adoption and impact are well documented, although the rarity at which these methods are applied to the use of predictive systems likely undervalues the impact of these systems in disease and crop management.

UTILITY OF PREDICTIVE SYSTEMS

The utility of predictive systems can be assessed on the basis of three potentially overlapping aspects: conceptual utility, developmental utility, and output utility (5, 41). Conceptual utility refers to the utility of a model as a frame of reference for thought. This is the foundation for articulating mental models and communicating concepts. All predictive systems should have some measure of conceptual utility.

Developmental utility refers to training of the modeler, as distinct from the disease manager, in thinking about a pathosystem. This utility can be exemplified by simulation models developed as research tools (11) and is applied in clarifying epidemic development, in testing hypotheses, in making predictions, and in shaping research directions (e.g., see 57).

Output utility is the usefulness of a model in its application by practitioners, be they farmers, their advisers, or policy makers. Predictive systems developed to justify inputs or satisfy regulatory mandates, to prioritize resource allocation, to reduce pesticide use, or to improve disease control are examples of output utility. Output utility obviously is desired in applied research and is the primary focus of this review.

What Is the Expectation for Adoption of Innovations in Agriculture?

The general perception of low adoption rate for predictive systems is not unique to plant pathology, and slow uptake or nonsustained use of computer models and decision support systems is found across diverse disciplines (34, 52, 64, 65, 66, 115). As early as the 1960s, a disconnect between business management science and business managers was recognized, a so-called practicality gap (37). Little (52) stated: "The big problem with management science models is that managers practically never use them. There have been a few applications, of course, but the practice is a pallid picture of

THE BASS INNOVATION DIFFUSION MODEL

Let N be the number of potential adopters in the population and $A(t)$ be the number of adopters at time, t. The rate of adoption from innovation is defined as

$$\frac{dA(t)_{in}}{dt} = p \cdot [N - A(t)]. \qquad 1.$$

The rate of adoption arising from contact (sometimes referred to as the rate arising from imitation) within the adopting population is

$$\frac{dA(t)_{im}}{dt} = q \cdot A(t) \cdot [N - A(t)]. \qquad 2.$$

The full Bass (4) model combines these rates:

$$\frac{d\,A(t)}{dt} = p \cdot [N - A(t)] + q \cdot A(t) \cdot [N - A(t)]. \qquad 3.$$

The right-hand side of Equation 1 is a decreasing exponential function of the number of adopters, $A(t)$. At the start of the adoption process, when $A(t) = 0$, Equation 1 simply gives the initial fraction of innovating adopters. This is equivalent to Rodgers's (89) fraction of true innovators. Because $dA(t)_{in}/dt$ declines rapidly as $A(t)$ increases and p (coefficient of innovation) is typically one to two orders of magnitude smaller than q (coefficient of imitation) (104), the Bass model can be simplified to include only Equation 2, which is simply a logistic growth curve. In this case, an initial fraction of adopters must still be assumed or there is no adoption process [as setting $A(t)$ to zero in Equation 2 easily demonstrates]. Adoption curves based on the results of Sultan et al. (104) are presented in **Figure 1**. The full model has its maximum rate of adoption at 6.2 years, and the reduced model has its maximum rate at 6.6 years. Meade & Islam (72) give a comprehensive review of the development and elaboration of adoption diffusion models.

the promise." Thirty-five years later, a review of decision support systems in information technology (IT) suggested the professional and practical contribution of decision support research "is facing a crisis of relevance" (3). The European Federation of Information Technology in Agriculture devotes multiple sessions at its biennial congress to the subject of improving IT adoption (**http://www.EFITA.net**). At the 2009 congress, Gelb & Voet (28) reported the results of survey questionnaires completed by attendees during 2001 and 2007. The percentage of attendees who believed there were problems with uptake of information and communication technologies (ICTs) in agriculture increased from approximately 50% to approximately 95%.

Adoption (or nonadoption) of innovations of disease predictive systems is a specific case of a generic issue that has been discussed in general terms by Rodgers (89), in an agricultural science context by McCown (66) (with focus on decision support systems), and within agricultural pest management in relation to uptake of IPM (25, 71, 109, 116). Developers of predictive systems may conclude that predictive systems are underutilized either because these systems are, in fact, not widely used, or because assessment methods (and resulting data) give inadequate measures of adoption, use, and impact (87). This situation suggests the need for a simple benchmark against which adoption of a particular piece of technology can be assessed.

One possible solution is suggested by the work of Sultan et al. (103, 104) on the Bass (4, 61) model for diffusion (i.e., adoption) of innovations (see sidebar, The Bass Innovation Diffusion Model). The model contains rate parameters for adoption that result from factors external to an innovation (the coefficient of innovation; e.g., from advertising by extension workers), and for adoption resulting from internal influences (the coefficient of imitation; e.g., word-of-mouth recommendation or imitation). Sultan et al. (104) pooled results for studies of diffusion from 213 technology innovations from different sectors of society. The rate parameters estimated for these different pieces of technology showed some interesting qualitative similarities, the most obvious of which was the tendency for the rate parameters associated with factors external to an innovation, p, to be approximately 10 times smaller than the corresponding parameter, q, which is associated with imitation, or similar processes that result from interaction among potential adopters. The ratio between p and q tends to be even smaller with many agricultural innovations. In a study of adoption of pesticide application among Nigerian cocoa growers (1), the maximum likelihood estimates for p and q were 0.004 and 0.355, respectively, which are consistent with the greater relative importance of imitation than innovation as obtained in the meta-analysis of Sultan et al. (104) for nonagricultural technologies.

A few important reference points can be drawn from this type of analysis. First, the timescale required to assess adoption (see **Figure 1**) is likely to be longer than typical research grant life spans: The maximum adoption rate in the empirical example discussed (1) occurred after more than six years, and reaching 80% adoption would take more than a decade. Timescales for adoption have implications for the way adoption studies are funded and conducted and suggest a need to raise awareness among funders to ensure that suitable funding processes are made available. Currently, many assessments of adoption of predictive systems are focused on short timescales with simple measurement instruments, such as surveys, that consider direct consultation of a system but may fail to recognize the importance of selective adoption (88) of the concepts embedded in predictive systems and diffusion through secondary sources. Long-term data sets showing improvements in management efficiency associated with use of a predictive system are rarely collected and, where available, can be difficult to interpret objectively (122).

A second implication of the analysis concerns the structure of the model and the associated assumptions about underlying processes. The Bass model is a mass action or complete mixing model that assumes that at any point in time all adopters, $A(t)$, and nonadopters, $[N{-}A(t)]$, interact. This is obviously an unrealistic assumption (see the discussion on social network structure below), but when the model parameters are estimated from data, the estimated values adjust to the data and model the outcome of the actual, but unobserved, process as if it operated by mass action. Akinola (1) discussed the impact that segregation within the adopting population could have on the rate of adoption but analyzed the issue by assuming that the segregation is between innovators and imitators. McRoberts & Franke (68) developed a more general approach that allows for incomplete mixing (i.e., aggregation, stratification, or substructuring) in the adopting population but retains the basic diffusion model approach. Chatterjee & Eliashberg (14), van den Bulte & Stremersch (110), and Meade & Islam (72) give detailed analyses of the issue of heterogeneity in the adopting population and its potential impacts on adoption.

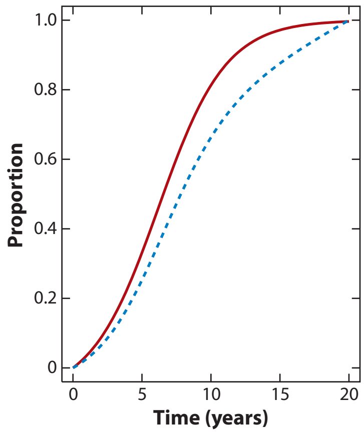

Figure 1

Adoption curves based on the results of Sultan et al. (104). The solid red line is the curve generated by their mean parameter estimates of $p = 0.03$ and $q = 0.38$. The dashed blue line is the curve corresponding to a single initial innovation event with $pN = p$ innovators.

Deviation from the assumption of complete mixing in real populations can be studied by using the tools of social network analysis. For a population of N potential adopters, complete mixing models assume that all $[N(N{-}1)]/2 \approx N^2/2$ connections among individuals exist. In real networks, the level of connectivity is usually much less than this and the level of connection varies greatly among individuals. In such situations, the potential for exchange between adopters and nonadopters depends not only on how many of each there are in the population but also on who they are and who they know. Data from Hoffman et al. (36) illustrate these points (**Figure 2**). Hoffman et al. (36) surveyed grape growers in Lodi, California on their perceptions of the usefulness of different

Selective adoption: limited or partial adoption of a concept or product. May occur even when benefits of an innovation have been proven

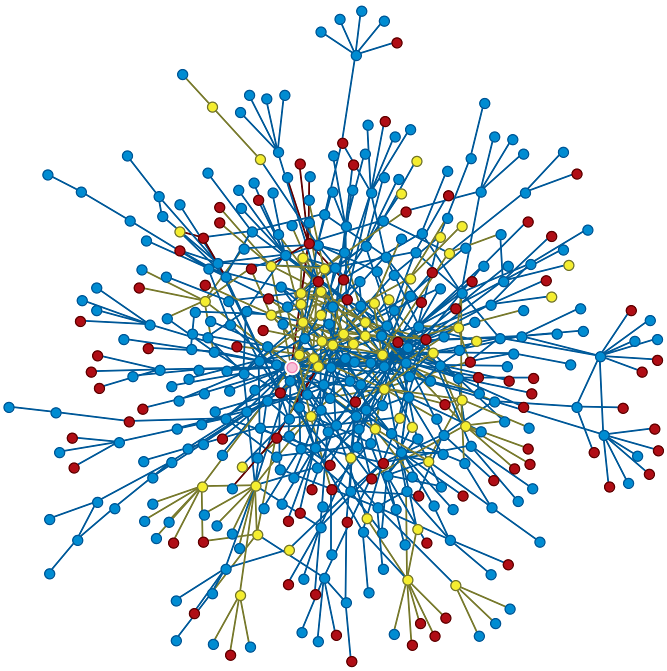

Figure 2

A knowledge-sharing network for viticulture management practices among grape growers and outreach professionals in Lodi, California (36). Points represent individuals and lines represent communication and knowledge sharing. The pink point is a cooperative extension farm adviser, yellow points are growers that are also outreach professionals, red points are outreach professionals, and blue points are growers. Individuals with higher centrality scores are physically located closer to the center of the network. Figure redrawn by and used with the permission of Hoffman et al. (36).

Diffusion network: members of a social system that communicate information through formal and informal connections and interactions

sources of information on viticulture management and analyzed knowledge dissemination through a network of growers and outreach professionals. Personal relationships with information purveyors were among the most important factors in management decisions. Each respondent was asked to name up to four growers and four other people with whom they discussed vineyard management. There were 210 respondents, so a network that allows for every possible contact requires approximately 22,000 connections. Casual inspection of the diffusion network in **Figure 2** shows that the level of connectivity in the population was much lower than this. The knowledge-sharing network constructed for this population also illustrates the concept that management recommendations obtained by use of a particular technology can flow indirectly, via intermediaries, to users who may not realize the original source of the information. This indirect dissemination of information adds complexity to inferring adoption and use of a particular technology. Recent approaches to the study of person-to-person spread of human diseases in social networks (112), which combine diffusion models with dynamic network architecture, offer interesting possibilities for improved understanding of the analogous processes of person-to-person spread of innovations.

There are technologies that are not adopted for various reasons, and predictive systems (or their recommendations) may be rejected or reinvented if they do not fit the needs of the users, as described below. When predictive systems recommendations are adopted, it is common for information to be disseminated through social networks of extension educators, private crop advisers, and farmers (e.g., see 12, 45). Carroll et al. (12) reported that disease predictions from a regional weather network indirectly reach more than 1,800 farmers across New York, Pennsylvania, and New England through extension educators' activities. In 2011, a Fire Blight Alert page that delivers results of the CougarBlight model was active from mid-April to early June and was viewed by 672 individuals an average of 21 times each, whereas the other fire blight–related web pages covering various fire blight topics had approximately 10,000 views from 9,500 individuals, essentially one view per person (T. Smith, personal communication). This indicates that a subset of individuals (presumably consultants) are highly interested on a regular basis in what the CougarBlight model is indicating as the season progresses, and a larger group may be receiving this information. Assessing uptake in this type of situation, which is presumably common to many predictive systems, obviously requires more than a simple head count of unique direct users.

Evidence of the integration of predictive system disease warnings into the recommendations given by extension educators and private crop advisers is widely supported by reported data (see sidebar, Dissemination of Model Predictions Through Intermediaries). For example, 80% of consultants found the Danish pest management decision support system PC-Plant Protection of "average to very great usefulness" in direct advising of clients (77). Similarly, among Oregon tree fruit producers less than 31% of growers visited a decision support website during the growing season, whereas 87% of crop advisers did (13). Almost all growers (90%) rated consultants as somewhat (5%) to very important (63%) sources of information. Over half of the risk predictions issued by the *Fusarium* head blight forecasting system for wheat are used for advising others (21).

Bearing the preceding points in mind, any generalization that predictive systems are underutilized is likely to miss the point that many predictive systems were directly used by some individuals in some form for a certain period of time (66). The situation is further complicated with a decision aid because gauging its impact should assess more than its direct use: Evaluation should also include what concepts were learned and subsequently applied without further direct consultation of the system.

DISSEMINATION OF MODEL PREDICTIONS THROUGH INTERMEDIARIES

Dissemination of information through intermediaries, as shown above, is an important point to consider if implementation of a predictive system is desired. Extension advisers and consultants are a primary source of information for pest management in modern agricultural systems (49, 97) and perhaps the ultimate integrator of predictive systems into the unique constraints and objectives of potential users. Dissemination of predictions through crop advisers may lead to inherent issues of double risk response asymmetry if advisers impose their own aversion of risk into their recommendations (33), and this mode of delivery alone does not guarantee an improved management outcome. Nonetheless, the concept of a disinterested artificially intelligent superconsultant (60) has not proved successful or sustainable in business management or predictive systems in agriculture, and we suggest there is a lesson here for developing successful predictive systems for plant disease management. Although advancing technology continues to enhance IPM and consultant capabilities, it is not likely to replace consultants (90).

WHY IS DIRECT USE OF PREDICTIVE SYSTEMS NOT MORE WIDESPREAD AMONG FARMERS?

A partial answer to the question why use of predictive systems is not more widespread lies in the evidence presented already: The information may often be made available indirectly through other people in farmers' decision networks. The survey questionnaire results presented by Gelb & Voet (28) and Hochman & Carberry (34) also indicate opinions among researchers and stakeholders about the underlying reasons for implementation are varied and lack consensus. The reasons for nonadoption are primarily associated with social, logistical, and economic factors (34, 65, 66), as discussed in part below.

The Context of Farm Management Decision Making

In understanding use or nonuse of predictive systems by farmers it is essential to be aware of the overall context of farm management decision making and most importantly that it is situation dependent (9, 80, 81, 117). It is also important to question whether a new predictive system offers a perceivable benefit over current alternatives or a sufficient marginal benefit to justify any extra complexity in the decision process (56, 69, 93). Öhlmér and coworkers (80, 81) point out that farmers' decision-making processes often involve cyclic, iterative, and partly intuitive processes that are at odds with the empirical and linear problem decomposition and resolution approach implicit in the way that many decision aids are constructed. Technology that could be incorporated easily into the actual decision-making processes of farmers would ideally be sufficiently simple to be used quickly without overtaxing users' time or processing capabilities, or superseding other essential farm activities.

As an example of the complexity of disease management decision making and the type of context into which predictive systems need to fit, consider apple scab in the northeastern United States. Ascospore detection, pseudothecia maturity evaluations, and the Mills table (73) continue to be used as aids in timing fungicide applications, either directly or via recommendations from advisers. A 2012 survey of apple growers and consultants conducted by the Pennsylvania State University Extension found that 38.5% of respondents planned to maintain weather records and follow a disease prediction model for apple scab, and 50% of respondents planned to subscribe or currently subscribed to a disease, weather, or pest prediction service (A. R. Biggs, unpublished data). How the growers actually integrate scab predictions into their management is not fully clear, but any individual decision to apply/not apply a fungicide is the result of multiple sets of circumstances (D. Rosenberger, personal communication). The decision to make a treatment for apple scab is based on considerations such as crop developmental stage, the severity of scab the previous year, the likelihood of rain, and the availability of equipment to cover all of the orchards on a farm. For example, if heavy rains are forecasted during a model-predicted period of ascospore release, growers may increase the rates of products applied so as to have better residual activity through a long rainy period. However, if the need for an application is borderline (e.g., 20% chance of showers and the last application was applied only five days prior), then growers may wait until after a weather front passes, check their own instrumentation or listen for advice from an adviser, and then apply a different fungicide with postinfection activity if there actually was a significant scab infection event. During these uncertain periods, apple scab predictions may be consulted retrospectively to determine whether an infection event actually occurred. If no infection period was recorded and disease scouting indicates sufficiently low primary scab infections, the next decision may be delayed until just before the next forecasted wetting event. Decisions on tank mixes of protectant and eradicant fungicides and timing of subsequent applications are modified when other diseases, such as powdery mildew, rust diseases, or sooty blotch, threaten. The timing of a particular fungicide application then becomes a compromise of risk and benefits influenced by other factors, such as current and forecasted weather, equipment and fungicide availability, fungicide sensitivity of the pathogen, and shifting market conditions. Past management decisions and their consequences may be updated by disease predictions, field scouting information, changing weather, crop development, and changing crop price. Nonbiological aspects of apple scab management come into play as well, such as an individual farmer's goals, task scheduling, financial ability to suffer a financial loss from an incorrect decision, and perhaps marketing. Farmers also obtain information from a variety of sources—consultants, extension educators, and neighboring farmers—and scab predictions may be embedded in the management recommendations they receive. It is therefore difficult to isolate the contribution of a predictive system apart from its context of actual use, where it may be an important but certainly not the sole component in a series of decisions (86).

Given the context of decision making, it is not surprising that farmers' personal experience and relationships to information purveyors are among the most important considerations in their farm management decisions (36, 64, 97). Consequently, predictive systems must have high value in farmers' decision-making processes, or those of their advisers, to be sure of gaining acceptance.

The basic premise for developing predictive systems is, in an analogy to economic concepts, a supply-side approach: Predictive systems are constructed to supply a latent demand among farmers, which researchers identify on the basis of perceived (by researchers) inefficiencies in disease management. The paradigm case is that a grower's limited knowledge of the true risk from disease leads to risk-averse behavior, such as excessive prophylactic pesticide application. Decision theoretic analyses are now used regularly to evaluate the benefits of evidence-based predictive systems (e.g., see 20, 23, 40, 69). Such analyses often use naïve decision rules as their baseline comparisons, for example, a decision rule assuming a priori that treatment is always needed, i.e., without reference to actual risk. These comparisons are useful when current farm practice is to use a calendar or other preprogrammed schedule of treatments, but it seems more likely that treatment decisions are heavily influenced by growers' experience-based judgments. For example, powdery mildew in hop production in Oregon and Washington (85) and grape production in California (22) shows that across populations of growers, fewer treatments may be used than would be recommended by predictive systems.

The issue of comparison between predictive systems and farmers' judgments concerns the comparison of two sorts of predictive system. The formal methods of decision analysis (31, 69, 118) can be used for this purpose as long as the relevant data are available. A major limitation to such comparisons in the past has been the lack of negative controls (i.e., information on what would have happened had treatment been withheld in situations in which it was recommended) from commercial crops.

Viewing the adoption process as a competitive replacement of experienced-based judgments by predictive systems also forces consideration that a predictive system must fit within the existing situational and iterative decision-making processes (71, 80, 81). This replacement process can be seen as involving two quantities: the marginal change in predictive accuracy (upon switching from personal judgment to a predictive system) and the marginal change in decision-making process complexity. McRoberts et al. (69) suggested that methods from statistical model selection might be adapted to provide an indicator to measure the trade-off that typically occurs between these two marginal quantities. When predictive accuracies are combined with error costs, expected economic gains from adoption can be estimated (23, 31, 69). In general, these analyses indicate that highly accurate decision rules are needed to substantially reduce disease-related costs (both inputs and crop damage) compared with routine applications (23). Worse still, quantifying accuracy is complicated for certain disease predictors (86). Even without a full analysis of expected cost, calculation of error cost ratios (58, 59, 69) can reveal a great deal about the financial incentives (or lack thereof) for adopting a predictive system. Often these cost ratios are very small for high value crops (e.g., see 30, 83) and appear to justify prophylactic applications to obviate the risk of false negative predictions. However, false negative prediction errors can have less costly impacts in lower value crops, e.g., the decision to apply a fungicide for *Fusarium* head blight in wheat (58). Risk-averting behavior is common in pest management and many other decisions (e.g., see 76, 116), which adds further importance to a very high negative prediction accuracy. Achieving high negative prediction accuracy often comes at the expense of lower positive prediction accuracy.

Further insight into these issues can also be gained from calculating the formal expected information content of a predictive system relative to the current beliefs of the adopters (40, 71). Such calculations provide a formal basis for the intuitions that predictive systems have the greatest value (relative to judgments) when uncertainty about the future is highest and when decision makers have relatively uninformed prior beliefs about the future, and have the least value when they confirm existing beliefs. Technology acceptance models (see **Figure 1** and above) indicate that the primary component influencing the use of an information system is perceived usefulness, mostly through direct effects but also indirectly on attitudes toward using a system (18, 19). Determinants of perceived usefulness may include perceived risk (53) and social influences (111; see sidebar, Perceptions of Disease Risks and Use of Predictive Systems).

Cost ratio: relative cost of mistaken decision to treat compared with the cost of a mistaken decision to not treat

Negative prediction accuracy: the probability that a negative prediction is truly negative

Positive prediction accuracy: the probability that a positive prediction is true

PERCEPTIONS OF DISEASE RISKS AND USE OF PREDICTIVE SYSTEMS

Risk perception associated with using a predictive system varies among individuals depending on their views and preferences for risk, although risk perception is poorly understood in this context. Risk perceptions have neurological and affective components, vary among individuals in a population, and may be manifested without individuals being fully aware of the basis of their risk-avoiding decisions (92, 98, 114). They also may not be in line with actual risk (a misalignment termed probability neglect) (105): Personal judgments of risk and benefit are confounded and inversely related (2). Predictive systems may have instructive roles in informing disease risks, thereby decreasing probability neglect. The pest and disease warning system for wheat, EPIPRE, is a classic example of a predictive system (119, 121) that created learning opportunities that altered perceptions of disease risk. An important consideration is that in many instances farmers may face ambiguity rather than risk. In ambiguous situations, probabilities are unknown and calculation of risk and optimal actions are therefore impossible (39). Farmers' management decisions tend to be more constrained by uncertain expectations about the environment than their ability to derive an optimal management response given their resources (94). Thus, for predictive systems to be utilized over time they need to be informative and need to reduce management uncertainty without being redundant to a farmer's intuition.

Learning by Experience and the Life Span of Predictive Systems

Farmer learning through experience guided by a predictive system can reduce the need for direct consultation of a system over time. For example, a target of a 50% reduction in pesticide use compared with a set of reference years was legally imposed in Denmark during the 1990s. The computerized decision support system PC-Plant Protection was developed to help farmers implement the necessary changes in practice. The system was widely, but by no means ubiquitously, used. In cereal crops, the frequency of treatment and dosage of fungicides declined steadily over the past 20 years such that the average application intensity is statistically similar to those obtained by using the decision support system Crop Protection Online (95), suggesting that the availability of the system helped to move the reference point for standard practice across the population.

In many instances, experience leads to satisfactory management outcomes that can approach those generated by a predictive system. The short direct-use life span of many models can be attributed to the models teaching growers, who then intuitively or intentionally develop simple rules that lead to similar, adequate management decisions. Systems are used only as long as they are deemed useful, but the knowledge contained in the system is learned and enables disease risks to be estimated without direct consultation of the tool. Such examples include EPIPRE (27, 119), the Polley Period for powdery mildew on barley (detailed in 33), Crop Protection Online (46), and the HOPS powdery mildew risk index (29).

Similar patterns of a useful life span of other predictive systems in agriculture appear. As farmers used the FARMSCAPE crop production simulator, they developed simplified management rules and management approaches that reduced their need for the simulator that led to these management changes (67). The SIRATAC decision support system for insect pest management in cotton was initially adopted by 25% of Australian cotton farmers and utilized to manage insect pests on 40% of the cotton acreage, saving up to two insecticide applications annually compared with standard practices (16). The justification for continued support for SIRATAC was less clear when similar patterns of insecticide use developed without using the system. Some consider that learning and simplified management without use of SIRATAC was a system failure (75). However, given that system use resulted in a change in grower behavior and the desired outcome (improved management) (66), defining success and failure (or acceptable or unacceptable impact) is not straightforward. In these examples, the development and deployment of predictive systems apparently helped to create opportunities for accelerated farmer learning by experience and, critically, improved management, which is a measure of success in applied farm systems research (5).

Accuracy is requisite for usefulness of a predictor, although the economic consequences of positive prediction accuracy versus negative prediction accuracy typically are different. To be useful in practice, the necessary accuracy of a predictive system also depends on the degree to which a given disease biology and control technology allows for subsequent recovery from an incorrect negative disease warning, for example, by future disease scouting and corrective sprays with a fungicide. Drawing the preceding overview together, we suggest that it is possible to define broad types of situations between which we might expect the requirements and dynamics of adoption for predictive systems to differ. For polycyclic diseases with rapid epidemic velocities, low cost ratios, and the potential to cause irreversible crop damage or quality defects in the harvested product, there is little time between prediction and the need for economically critical action. In such cases, accurate and timely predictions are extremely important. Diseases of this type include grape powdery mildew, fire blight, tomato late blight, and *Botrytis* fruit rot on strawberry. When such diseases occur annually or are only one of a complex of other diseases or pests that require routine treatment, the need for accuracy is unchanged. However, the utility of the predictor may be diminished because of the small marginal cost of the additional coscheduled treatment or the significant marginal cost of deviations from the existing schedule.

In contrast, less stringent constraints are imposed on predictive system accuracy for diseases that are slow and steady in their development, have cost ratios closer to (or greater than) 1, have continuously varying quantitative effects on yield rather than severe economic consequences on quality, and allow for recourse following a false negative disease prediction. Examples include Stewart's wilt on corn or early leaf spot of peanut, and examples that are intermediate but tend toward this less-exacting end of the spectrum could include stem rust on perennial ryegrass, wheat stripe rust, or potato early blight. Utility of a disease predictor in this less stringent scenario also would be increased if routine applications are not made for other diseases/pests and/or if timing and severity of the subject disease differ substantially from year to year.

Because of the importance of perceived usefulness in adoption, several critical questions should be asked when developing or evaluating a predictive system: As currently managed, does a disease constrain yield or quality, is disease control unreliable, and are current approaches economically unsustainable? What new information beyond the growers' current skill and experience does a predictive system provide? How is the management outcome perceived as being improved (or diminished) by the predictive system compared with current practices? Is it possible to implement recommendations from a predictive system within the constraints and logistics of overall crop management? To answer these questions an understanding of the intended users' current management practices and constraints is essential because growers often have a baseline level of management skill that might be adequate without a predictive system.

It is not in all cases essential that a new predictive system fit seamlessly with existing management practices. Although technology is more readily adopted if current practices can be left largely intact, modifications of current practices can be reasonably expected to be adopted if the new predictive system meets a critical need in an efficient and effective manner. The motivation for developing predictive systems quite often comes from an implicit or explicit policy objective, such as pesticide use reduction (70). The development of BLITECAST and PC-Plant Protection are clear examples. Often research efforts are directed to crops that receive a large number of applications, which tend to be high value crops such as fruit and vegetables (see 20, 57). Under such circumstances, widespread adoption is intended to achieve an objective at one scale (say national reduction in pesticide use) through the aggregate effect on a sufficient proportion of individuals (i.e., farmers) making

A PREDICTIVE SYSTEM IS NOT NEEDED IN SOME CASES

There are many instances when a predictive system should not be developed (5). Many problems can be solved very well without a predictive system (79), as illustrated by success stories such as IPM programs in cotton in the southwestern United States (78), rice in the Mekong Delta (38), and ray blight disease of pyrethrum in Tasmania (84). In an entomology context, implementation of an insecticide resistance management strategy to address pyrethroid resistance in cotton production in Australia presented an alternative to the SIRATAC decision support system (17). Insecticide resistance management required restricting use of certain classes of insecticide to defined points in the season without necessarily consulting a predictive system. Cox (16) suggested that the success of this approach to pest management was because it was a social technology, depending on participation of, negotiation between, and commitment by many sectors of the cotton industry.

decisions at a lower scale. The risks and benefits of using a predictor may not be equally shared at each scale though (93). McRoberts et al. (70) developed sets of questions for policy makers and growers that they could usefully ask to set research priorities and discern whether it is advisable to invest in the development of a predictive system to achieve a policy objective. Such an approach could help to reduce the frequency of failed uptake of predictive systems and of failure to meet policy objectives (see sidebar, A Predictive System Is Not Needed in Some Cases).

MARGINAL BENEFITS, COSTS, AND SUSTAINED USE OF PREDICTIVE SYSTEMS

It is not always the case that experience and learning obviate the need for a direct use of a predictive system. There are notable exceptions where predictive systems continue to be used to a high degree long after their development. The longevity of some predictive systems appears to be correlated with the marginal benefits that are attainable primarily or solely through direct consultation of the system. Direct consultation of the system may be essential to realize these benefits because, for example, the nature of a pathosystem makes learning by experience difficult, the cost ratio associated with incorrect management decisions is extreme, or regulatory pressures mandate justification or reduction of pesticide applications.

Evidence for this assertion can be seen in several examples. A powdery mildew risk index for grape was originally designed to prescribe fungicide application intervals. Initially, use of the index in California reportedly reduced fungicide applications by two to three per vineyard per season with equal or better disease control compared with prophylactic treatment (32). Adoption of this index has increased steadily since 1996, and in 2008 50% of California growers self-reported as using the index heavily, often, or sometimes (54); Oregon and Washington growers reported 54% and 69% use, respectively, in 2011 and 2012 surveys (G. Grove & W. Mahaffee, unpublished results).

What characterizes growers' choice to use or not use the powdery mildew risk index? Lybbert & Gubler (54) found that among those not using the index, the primary reason cited for nonuse was a preference for a set application schedule. In contrast, users of the risk index cited better disease control as a primary motivation for adoption. Users did not assign greater importance to chemical cost savings than nonusers did, which is similar to responses in Oregon and Washington (**Figure 3**).

Lybbert et al. (55) further examined how growers use the risk index. Survey data from growers on their use of the risk index was combined with pesticide use data from the California Department of Pesticide Regulation database and daily weather data throughout grape-growing regions in California since 1996. Daily fungicide use was tracked and modeled in relation to powdery mildew risk index values and reported use of the index. These data indicated that growers' disease management strategies were indeed correlated

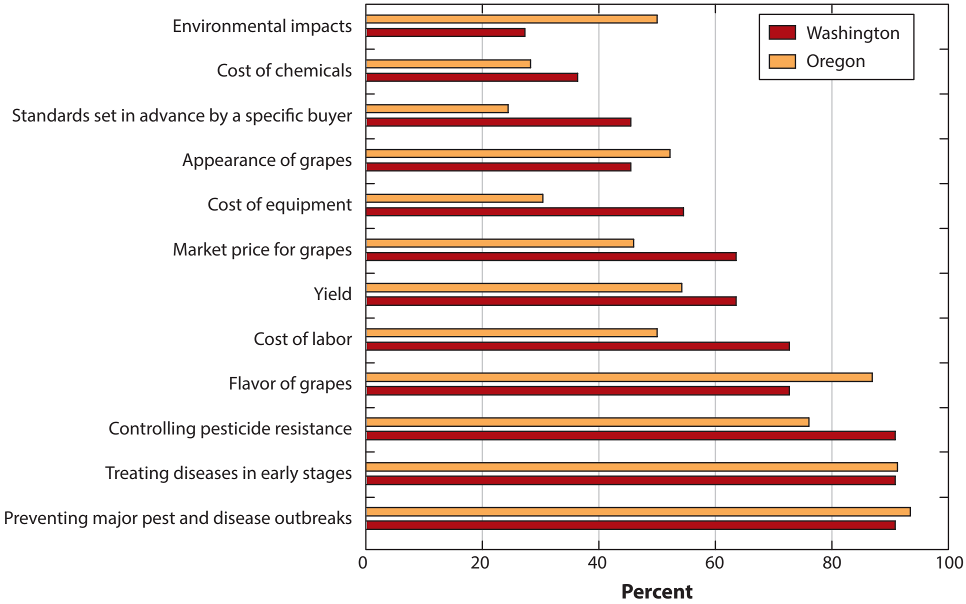

Figure 3

Percent of grape growers in Oregon and Washington rating management considerations as "extremely important" (G. Grove & W. Mahaffee, unpublished results).

with existing risk index levels (whether or not the growers were aware of the index values), but growers' responses varied among production regions and were highly nonlinear compared with risk index levels. Some users altered application intervals on the basis of the risk index level. Many nonusers of the index also varied their application intervals as conditions changed, presumably on the basis of their intuition, recommendations from advisers, or observation of neighbors. Depending on the production region, users of the index were more likely than nonusers to actively switch from sulfur to synthetic fungicides, to utilize more fungicide mixtures, and to increase fungicide rates at times when risk index values increased. Index forecasts of high risk resulted in the most aggressive application treatments by self-reported index users, especially in higher value grape production regions. The net effect is that users of the risk index utilized more fungicides overall and more synthetic fungicide mixtures compared with nonusers.

Powdery mildew is a primary management concern for wine grape growers, especially in high value production situations, and the surveys from California, Oregon, and Washington indicate that the majority of grape growers do consult the powdery mildew risk index in their management of powdery mildew. However, these surveys also reveal that growers place more importance on preventing major disease outbreaks than reducing chemical costs. The analysis of Lybbert et al. (55) indicates growers in California use the powdery mildew index as a risk management tool that minimizes the chance of severe disease outbreaks. For high value crops where premiums are paid for crop quality, the marginal benefits from using a predictive system that reduces the risk of costly disease outbreaks may be sufficient to encourage its sustained use.

Consider also fire blight as an example of a disease in which incorrect management decisions have substantial financial impacts. Several predictive systems for fire blight have been developed (e.g., see 6, 99, 100, 101). In general, these models identify periods conducive to epiphytic growth of *Erwinia amylovora* and its spread among blossoms, producing the populations needed for infection to occur. Several predictive systems continue to be utilized extensively for disease management (26, 45). In Washington State, the CougarBlight model (99) was implemented on the Washington State University Decision Aid System and was consulted by 79% of the Decision Aid System users (45). The users represent a large portion or majority of the tree fruit industry, either directly as farmers or indirectly through their management recommendations (45). In the mid-Atlantic region of the United States, Maryblyt predictions and their interpretation are central to disease warnings issued by research and extension personnel. Maryblyt is also used directly by individual growers and crop consultants for regional and site-specific fire blight hazard warnings. In Israel, use of the Fire Blight Control Advisory is reported to have greatly reduced the risk of fire blight to the pear industry. This system is reported to be used extensively, and its use parallels a reduced frequency of severe fire blight outbreaks in Israel (26).

Fire blight prediction systems improve disease control and reduce management uncertainty because their use generally results in acceptable disease control, which may not be true even with prophylactic applications (108). Some conditions that are favorable to fire blight are obvious to experienced growers, but other conditions are more difficult to identify precisely. The cost of an incorrect management decision for fire blight can be massive because of crop loss in the current season, increased pruning expenses, and the potential to lose entire trees. The difficulty of appropriately timing antibiotics in applications and the potential risk of significant economic losses appear to be primary drivers of the use of fire blight prediction systems. Although antibiotic use can be reduced in some situations, in other situations it is increased or unchanged compared with routine applications. Thus, the advantage conferred by fire blight predictors appears to be avoiding costs associated with poor disease control. The sustained use of certain fire blight forecasters indicates these predictors possess acceptable accuracy and aid in mitigating a critical management problem.

Forecasting systems that predict inoculum levels or arrival of inoculum also tend to inform decisions that are not readily learnable, and several such predictors have had sustained direct use. Cucurbit downy mildew and tobacco blue mold management in susceptible hosts is dependent on timely and repeated fungicide applications. A system for predicting tobacco blue mold in the eastern United States became publicly available in 1995, relying on an extensive reporting network of state representatives to identify disease occurrences in commercial fields and sentinel plots. A similar system for cucurbit downy mildew became operational in 1998 (63). In both systems, the location of disease outbreaks and weather forecast data are utilized to predict conditions favorable for transport and deposition of spores to enable near real-time mapping of disease risk levels (62, 63). Maps of disease occurrences and local commentary provide advice for epidemic conditions and support location-specific decisions, which may, if this information is reported from the source location, include information on host (indicating potential biotype of *Pseudoperonospora cubensis*) and fungicide sensitivity of the pathogen. Together, this information advises on the timing of the first fungicide application and, potentially, an appropriate fungicide (35, 82).

Both the tobacco blue mold and cucurbit downy mildew predictive systems continue to be used extensively for disease management. During the 2000 season, 743 tobacco blue mold forecasts were posted on the Blue Mold Forecast Center website, and more than 300,000 visits were made to the website (63). Ascertaining implementation of blue mold forecasts by farmers is difficult because the primary users of the system are extension educators and specialists, who in turn disseminate disease hazard warnings to their clientele by various means. However, blue mold predictions are a key aspect of disease hazard warnings issued by extension agents and other specialists. For example, in 2010 a disease warning issued for a county in North Carolina resulted in some 50,000 acres of tobacco in the affected and neighboring county being treated with a fungicide within 48 hours (A. Mila, personal communication).

As of May 2012, more than 250 individuals have signed up to receive automated cucurbit downy mildew alerts, including farmers (28% of users), industry personnel (7.1%), and crop advisers (7%) (82). A 2010 survey of registered users indicated that 49% used the forecasting website regularly, with 33% indicating that a past visit to the website had helped them prevent yield losses, and 57% indicating that the forecasting website and the alert system were very useful in their effort to control cucurbit downy mildew. Extension personnel in Georgia, North Carolina, and Michigan attributed to the forecasting system a saving of two to three fungicide applications in 2009 compared with calendar-based fungicide applications, an estimated savings of $6 million in fungicide costs (82).

Use of the downy mildew predictive systems provides information on a process that cannot be readily learned by experience and also substantially improves disease management. The outputs of this predictive system direct growers to initiate fungicide applications, which are a time-sensitive and integral component of preventing damaging outbreaks of the diseases and their spread (82). Although in some years fungicide applications may be reduced, use of the system substantially improves disease control and reduces the risk of damaging disease outbreaks in most years, indicating the motivation for use is related to improved risk management.

Sporadic occurrence of a disease limits the opportunities for learning by experience and may increase management uncertainty. In these situations, the marginal benefit of using a predictive system is greater because of both the risk avoidance and the financial savings of strategic timing of fungicides compared with routine applications. Sustained use of predictive systems is evidenced in such situations. Since the late 1990s, a late-blight warning system has been utilized in the Columbia Basin in the Pacific Northwest of the United States to predict the likelihood of a disease outbreak at a regional level (43). A seasonal probability of regional late-blight occurrence is estimated in early May on the basis of a long range rain forecast, which allows implementation of late-blight management tactics before foliage becomes overly dense. The advanced warning enables the first fungicide application to be made before the pathogen is introduced to most of the crop. Subsequent warnings use the probability of a late-blight outbreak, the weather forecasts, and crop canopy development to calculate a risk index to guide fungicide application intervals. The risk index outputs inform disease management recommendations issued by extension specialists and other advisers.

A 2011 survey that accounted for 53% of commercial potatoes grown in the Columbia Basin in 2010 (D. Johnson, personal communication) indicated that 41% of polled growers accessed the late-blight information telephone line two to three times per week, 32% accessed it once per week, 14% accessed it two to three times per month, 5% accessed it once per month, and 8% accessed it once per season. The information was likely utilized by an even larger audience given that most of the respondents indicated that they shared the information with others.

Sustained use of the forecasting system in the Columbia Basin can be contrasted with the fate of BLITECAST (51, 57) or late-blight predictors in certain European countries. Late-blight predictors appear to have less direct use in situations in which late blight occurs annually and statutory requirements for pesticide use reduction do not limit prophylactic fungicide applications (15). These examples suggest that predictive systems for late blight have prolonged use when their recommendations improve control of the disease, reduce management uncertainty, or achieve regulatory compliance (15). Farmers use pesticides to both maximize return on investment and as insurance against disease control failures

(24, 76). The marginal benefits associated with savings in fungicide applications alone do not appear sufficient to encourage use of late-blight predictors in regions where other factors do not limit the utility or deployment of standard management practices.

From these case examples, a common theme emerges from predictive systems that have had sustained, direct use over time. We assume that acceptable accuracy of disease predictions and infrastructure for calculation and dissemination of the disease predictors are minimal requirements for sustained use of a predictive system. Clearly, these are not trivial requirements. However, sustained direct use of predictors also appears to involve informing a decision process that is difficult to learn from experience but improves a decision that is imperative for crop management, such as reducing the risk of serious crop damage. Analogous situations also occur in entomology, where forecasting models for insects have found the greatest application where the use and timing of insecticides are critical, such as temperature-driven models for pheromone monitoring of codling moth (115).

CONCLUSIONS

The literature based on development of disease predictive systems is extensive and diverse, and stands in contrast to the paucity of literature on the use and impact of these systems in practical disease management. In 1952, Miller & O'Brien (74) stated "A great deal of work has been done on topics included in the range of interest of forecasting, but which so far has not been put to actual use in practical forecasting." Since then, much progress in disease prediction has been made, and now many examples of practical application can be cited. Several weather monitoring equipment companies also offer disease predictive systems software add-ons. The accuracy and availability of site-specific weather forecasts has improved substantially, and numerous private meteorologists now offer plant disease risk predictions. Some disease forecasters are delivered to farmers as a technology cluster along with soil moisture monitoring and weather monitoring services (107). Never before has information delivery been more rapid or readily available. Trends in research indicate that effort to evaluate and apply predictive systems is much greater than just a few decades ago (20).

Although there is evidence of sustained direct use of predictive systems in several pathosystems, the majority of predictive systems appear to be adopted directly by only a minority of growers and often for a limited duration. Their usefulness and impact on disease management is mostly indirect by means of farmer education and by informing growers' advisers. The degree that predictive systems are used in this role appears varied depending on the amount of perceived new, actionable information consistent with the objectives of the adviser and farmers. These objectives commonly involve avoiding risks associated with costly disease outbreaks and improving yield as well as other factors beyond solely reducing pesticide use.

Perhaps two lessons for developers of predictive systems are to make decision aids learnable and to judge success on the basis of changes in users' management skills rather than their consultation of a system. Predictive systems may look very different if their purpose is to facilitate learning that eventually makes the tool obsolete for experienced farmers. Issues of long-term maintenance and support of certain predictive systems (34) may become less problematic if a system also comes with an explicit expiration date linked to an achievable management objective. We hope that this review emphasizes that the role and impact of predictive systems in plant pathology have sometimes been lost in simple head counts of self-reported use of a particular hardware or software. If ingrained ideas of disease risk are incorrect, a useful predictive system facilitates opportunities for farmers and their advisers to experience new ways of viewing their standard disease management practices. A learnable predictive system can be a tool to modify perceptions and practices, even if the tool itself is eventually ignored.

The examples presented indicate that very different approaches can be used successfully for disease prediction—contrast, for example, CougarBlight, the tobacco blue mold forecasting system, and the late-blight forecaster in the Pacific Northwest of the United States. A picture emerges of predictive systems being most successful when designed and deployed with an awareness of the context of farmers' decision-making processes, their constraints and objectives, and their current knowledge. The fit of a predictive system to the management problem faced by growers is the key to their use, a conclusion reached by others for implementation of IPM in general (91, 116). The continuing challenge for developers of predictive systems is to create tools relevant to the needs and constraints of farmers and their advisers that can provide learning opportunities and improve on their current management. In the long-term, this improvement may or may not involve routine consultation of the predictive system, depending on how readily its predictions can be learned. Thus, a requisite for designing and deploying a successful predictive system is an appreciation for farmers' decision-making processes in managing plant diseases and, more generally, their farm enterprises.

SUMMARY POINTS

1. Predictive system is a general term that refers to formalized algorithms that assess disease risk factors to inform the need for crop protection measures. There is no accepted structure for predictive systems, leading to a great diversity of these systems.
2. The research community often perceives adoption and use of predictive systems to be low, the so-called problem of implementation. This perception may reflect that these systems are not used to a large extent or that assessment methods were inadequate to objectively measure direct and indirect adoption, use, and impact. Few studies have attempted to rigorously quantify the use and impact of predictive systems in disease management. This situation suggests the need for a simple benchmark against which adoption of a particular piece of technology can be assessed. The Bass model for diffusion offers one possible solution for assessing adoption of predictive systems or the management concepts they encapsulate.
3. The justification often provided for developing or implementing a predictive system is a policy objective, such as pesticide use reduction. This justification seems misaligned with how management decisions are made by many farmers, who use pesticides to both maximize return on investment and as insurance against disease control failures. Predictive systems with sustained use tend to be those that improve management objectives when the correct decision is (currently) uncertain or difficult to estimate from experience/learning and is not necessarily related to pesticide use reduction alone. However, regulatory requirements for pesticide use reduction can be a motivating factor for the use of predictive systems.
4. To be successful, a predictive system must be sufficiently accurate to assure users that they do not risk a severe economic loss as a trade-off for what may be a relatively limited economic advantage of use. The level of predictive system accuracy needed to meet this requirement can differ greatly among pathosystems and is affected by such factors as epidemic velocity, cost ratio of false-negative to false-positive decisions, type of damage caused to harvestable crop, and the management tools available to make a later correction to an incorrect decision.

5. There is evidence of sustained use of predictive systems in several pathosystems, although predictive systems typically appear to be adopted directly by a minority of growers and often for a limited duration. They tend to be used as long as they are useful. In many instances, experience gained from using the predictive system leads to satisfactory management outcomes that can approach those generated by the system itself. The short operational life span of many models is attributed to learning by growers who intuitively or intentionally develop simple rules informed by their experiences with a predictive system that led to adequate management decisions.
6. The usefulness and impact of predictive systems in disease management is often indirect through farmer education and advising farmers' advisers. In this sense, dissemination of predictive systems outputs depends in part on a social network for information exchange and its implementation. The degree that predictive systems are used in this role varies depending on the amount of perceived new, actionable information consistent with the objectives of the adviser and farmers, which often involve avoiding risks associated with costly disease outbreaks.
7. The continuing challenge for predictive systems developers is to develop tools relevant to the needs and constraints of farmers and their advisers that can provide learning opportunities and improve on their current management skill. Thus, a requisite for designing and deploying a successful predictive system is an appreciation for farmers' decision-making processes in managing plant diseases and, more generally, their farm enterprises.

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. The use of trade, firm, or corporation names in this publication is for the information and convenience of the reader. Such use does not constitute an official endorsement or approval by the United States Department of Agriculture or the Agricultural Research Service of any product or service to the exclusion of others that may be suitable.

ACKNOWLEDGMENTS

We thank our colleagues in the Western Weather Work Group (Len Coop, Chris Daly, Alan Fox, Gary Grove, Doug Gubler, Paul Jepson, Dennis Johnson, Joyce Strand, and Carla Thomas) for discussions that influenced the content of this paper. Comments on a draft of this paper from Dennis Johnson and Ken Johnson were exceptionally helpful and appreciated. We also thank the numerous farmers and colleagues who shared their insights and experiences, with particular thanks to Alan R. Biggs, Erick De Wolf, Fred Geschwill, Pat Phipps, Dave Rosenberger, Howard Schwartz, Jim Steadman, Tim Smith, and Turner Sutton.

LITERATURE CITED

1. Akinola A. 1986. An application of the Bass model in the analysis of diffusion of coco spraying chemicals among Nigerian cocoa farmers. *J. Agric. Econ.* 37:395–404

2. Alhakami AS, Slovic P. 1994. A psychological study of the inverse relationship between perceived risk and perceived benefit. *Risk Anal.* 14:1085–96
3. Arnott D, Pervan G. 2005. A critical analysis of decision support systems research. *J. Inf. Technol.* 20:67–87
4. Bass F. 1969. A new product growth model for consumer durables. *Manag. Sci.* 15:215–27
5. Bennett D, Macpherson DK. 1985. Structuring a successful modeling activity. *Agric. Syst. Res. Dev. Ctries. Proc. Int. Workshop Hawkesbury Agricultural College, Richmond, N.S.W., Australia, May 12–15*, pp. 70–76. Canberra: ACIAR. 189 pp.
6. Billing E. 1996. BIS95, an improved approach to fire blight risk assessment. *Acta Hortic.* 411:121–26
7. Bouma E. 2007. Computer aids for plant protection, historical perspective and future developments. *EPPO Bull.* 37:247–54
8. Bourke PMA. 1970. Use of weather information in the prediction of plant disease epiphytotics. *Annu. Rev. Phytopathol.* 8:345–70
9. Brodt S, Klonsky K, Tourte L. 2006. Farmer goals and management styles: implications for advancing biologically based agriculture. *Agric. Syst.* 89:90–105
10. Butt DJ, Jeger JM. 1985. The practical implementation of models in crop disease management. In *Advances in Plant Pathology*, Vol. 3, ed. CA Gilligan, pp. 207–30. London: Academic. 255 pp.
11. Campbell LC, Madden LV. 1990. *Introduction to Plant Disease Epidemiology*. New York: John Wiley and Sons. 532 pp.
12. Carroll J, Weigle T, Petzoldt C. 2011. The network for environment and weather applications (NEWA). *N. Y. Fruit Q.* 19:5–9
13. Castagnoli SP. 2006. Internet-based decision tools for orchard pest management: adoption in the Hood River Valley of Oregon. *HortTechnology* 16:133–38
14. Chatterjee R, Eliashberg J. 1990. The innovation diffusion process in a heterogeneous population: a micromodeling approach. *Manag. Sci.* 36:1057–79
15. Cooke LR, Schepers H, Hermansen A, Bain RA, Bradshaw NJ, et al. 2011. Epidemiology and integrated control of potato late blight in Europe. *Potato Res.* 54:183–222
16. Cox PG. 1996. Some issues in the design of agricultural decision support systems. *Agric. Syst.* 52:355–81
17. Cox PG, Forrester NW. 1992. Economics of insecticide resistance management in *Heliothis armigera* (Lepidoptera: Noctuidae) in Australia. *J. Econ. Entomol.* 85:1539–50
18. Davis FD. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 13:319–40
19. Davis FD. 1993. User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *Int. J. Man-Mach. Stud.* 38:475–87
20. De Wolf ED, Isard SA. 2007. Disease cycle approach to plant disease prediction. *Annu. Rev. Phytopathol.* 45:203–20
21. De Wolf E, Shah D, Paul P, Madden L, Willyerd K, et al. 2010. Advances in the development and deployment of models for FHB and DON. In *Proc. 2010 Natl. Fusarium Head Blight Forum, Milwaukee*, Dec. 7–9, p. 79. Okemos, MI: ASAP Printing
22. Epstein L, Bassein S. 2003. Patterns of pesticide use in California and the implications for strategies for reduction of pesticides. *Annu. Rev. Phytopathol.* 41:351–75
23. Fabre F, Plantegenest M, Yuen J. 2007. Financial benefit of using crop protection decision rules over systematic spraying strategies. *Phytopathology* 97:1484–90
24. Fenemore PG, Norton GA. 1985. Problems of implementing improvements in pest control: a case study of apples in the UK. *Crop Prot.* 4:51–70
25. Fernandez-Cornejo J, Kackmeister A. 1996. The diffusion of integrated pest management. *J. Sustain. Agric.* 7:71–102
26. Forbes GA, Shtienberg D, Mizubuti E. 2009. Plant disease epidemiology and disease management: Has theory had an impact on practice? In *Integrated Pest Management: Innovation-Development Process*, ed. R Peshin, AK Dahwan, pp. 351–68. New York: Springer

27. Forrer HR. 1992. Experiences with the cereal disease forecast system EPIPRE in Switzerland and prospects for the use of diagnostics to monitor disease state. *Proc. BCPC Conf. Pests Dis.*, *Brighton, UK*, Nov. 23–26, pp. 711–20. Farnham, UK: British Crop Protection Council
28. Gelb E, Voet E. 2009. *ICT Adoption Trends in Agriculture: A Summary of the EFITA ICT Adoption Questionnaires* (*1999–2009*). Rehovot, Isr.: Hebr. Univ. of Jerus. Dep. Agric. Econ. Manag. **http://departments.agri.huji.ac.il/economics/voet-gelb.pdf**
29. Gent DH, Nelson ME, George AE, Grove GG, Mahaffee WF, et al. 2008. A decade of hop powdery mildew in the Pacific Northwest. *Plant Health Prog.* doi:10.1094/PHP-2008-0314-01-RV
30. Gent DH, Ocamb CM. 2009. Predicting infection risk of hop by *Pseudoperonspora humuli*. *Phytopathology* 99:1190–98
31. Gold HJ. 1989. Decision analytic modeling for plant disease control. In *Plant Disease Epidemiology*. Vol. 2: *Genetics, Resistance and Management*, ed. K Leonard, W Fry, pp. 84–122. New York: McGraw-Hill. 377 pp.
32. Gubler WD, Rademacher MR, Vasquez SJ, Thomas CS. 1999. Control of powdery mildew using the UC Davis powdery mildew risk index. *APSnet Features*. doi: 10.1094/APSnetFeature-1999-0199
33. Hardwick NV. 2006. Disease forecasting. In *The Epidemiology of Plant Diseases*, ed. BM Cooke, DG Jones, B Kaye, pp. 239–67. Dordrecht: Springer. 576 pp. 2nd ed.
34. Hochman Z, Carberry PS. 2011. Emerging consensus on desirable characteristics of tools to support farmers' management of climate risk in Australia. *Agric. Syst.* 104:441–50
35. Holmes GJ, Main CE, Keever ZT III. 2004. Cucurbit downy mildew: a unique pathosystem for disease forecasting. In *Advances in Downy Mildew Research*, Vol. 2, ed. PTN Spencer-Phillips, M Jeger, pp. 69–80. Dordrecht: Kluwer Acad. Publ. 288 pp.
36. Hoffman M, Lubell M, Hillis V. 2011. Learning pathways in viticulture management. *Res. Brief*, Cent. Environ. Policy Behav., Davis, CA. **http://environmentalpolicy.ucdavis.edu/files/cepb/Learning%20pathways%202011_1.pdf**
37. Howard RA. 1963. The practicality gap. *Manag. Sci.* 14:503–7
38. Huan NH, Mai V, Escalada MM, Heong KL. 1999. Changes in rice farmers' pest management in the Mekong Delta, Vietnam. *Crop Prot.* 18:557–63
39. Huettel SA, Stowe CJ, Gordon EM, Warner BT, Platt ML. 2006. Neural signatures of economic preference for risk and ambiguity. *Neuron* 49:765–75
40. Hughes G. 2012. *Applications of Information Theory to Epidemiology*. St. Paul, MN: APS Press. 158 pp.
41. Innis B. 1972. Simulation of ill-defined systems: some problems and progress. *Simul. Today* 9:33–36
42. Jacobsen BJ. 1997. Role of plant pathology in integrated pest management. *Annu. Rev. Phytopathol.* 35:373–91
43. Johnson DA, Hamm PB, Miller JS, Porter LD. 2012. Late blight epidemics in the Columbia Basin. In *Sustainable Potato Production: Global Case Studies*, ed. Z He, R Larkin, W Honeycutt, pp. 141–62. Dordrecht: Springer. 539 pp.
44. Johnson KB. 1987. The role of predictive systems in disease management. In *Crop Loss Assessment and Pest Management*, ed. PS Teng, pp. 176–90. St. Paul, MN: APS Press. 270 pp.
45. Jones VP, Brunner JF, Grove GG, Petit B, Tangren GV, Jones WE. 2010. A web-based decision support system to enhance IPM programs in Washington tree fruit. *Pest Manag. Sci.* 66:587–95
46. Jørgensen LN, Noe E, Nielsen GC, Jensen JE, Ørum JE, Pinnschmidt H. 2008. Problems with disseminating information on disease control in cereals to farmers. *Eur. J. Plant Pathol.* 121:303–12
47. Knight JD. 1997. The role of decision support systems in integrated crop protection. *Agric. Ecosyst. Environ.* 64:157–63
48. Kogan M. 1998. Integrated pest management: historical perspectives and contemporary developments. *Annu. Rev. Entomol.* 43:243–70
49. Koul O, Cuperus GW. 2007. Ecologically based integrated pest management: present concept and new solutions. In *Ecologically Based Pest Management*, ed. O Koul, G Cuperus, pp. 1–17. Oxfordshire, UK: CABI. 462 pp.
50. Krause RA, Massie LB. 1975. Predictive systems: modern approaches to disease control. *Annu. Rev. Phytopathol.* 13:31–47

51. Krause RA, Massie LB, Hyre RA. 1975. BLITECAST a computerized forecast of potato late blight. *Plant Dis. Rep.* 59:95–98
52. Little JDC. 1970. The concept of a decision calculus. *Manag. Sci.* 16:B466–85
53. Lu H-P, Hsu C-L, Hsu HY. 2005. An empirical study of the effect of perceived risk upon intention to use online applications. *Inf. Manag. Comput. Secur.* 13:106–20
54. Lybbert TJ, Gubler WD. 2008. California wine grape growers' use of powdery mildew forecasts. *Agric. Resour. Econ. Update* 11:11–14
55. Lybbert TJ, Magnan N, Gubler WD. 2012. *Powdery mildew forecasts and California wine grapes: How do growers respond to disease forecasts and to what environmental effect?* Work. Pap., Dep. Agric. Resour. Econ., Univ. Calif. Davis
56. Lynch T, Gregor S, Midmore D. 2000. Intelligent support systems in agriculture: How can we do better? *Aust. J. Exp. Agric.* 40:609–20
57. MacKenzie DR. 1984. BLITECAST in retrospect: a look at what was learned. *FAO Plant Prot. Bull.* 32:45–49
58. Madden LV. 2006. Botanical epidemiology: some key advances and its continuing role in disease management. *Eur. J. Plant Pathol.* 115:3–23
59. Madden LV, Hughes G, van den Bosch F. 2007. *The Study of Plant Disease Epidemics*. St. Paul, MN: APS Press. 421 pp.
60. Magarey RD, Travis JW, Russo JM, Seem RC, Magarey PA. 2002. Decision support systems: quenching the thirst. *Plant Dis.* 86:4–14
61. Mahajan V, Mueller E, Bass FM. 1995. Diffusion of new products: empirical generalizations and managerial uses. *Mark. Sci.* 14:G79–88
62. Main CE, Davis JM. 1989. Epidemiology and biometeorology of tobacco blue mold. In *Blue Mold of Tobacco*, ed. WE McKean, pp. 201–15. St. Paul, MN: APS Press. 288 pp.
63. Main CE, Keever T, Holmes GJ, Davis JM. 2001. Forecasting long-range transport of downy mildew spores and plant disease epidemics. *APSnet Features.* doi: 10.1094/APSnetFeature-2001-0501
64. Matthews KB, Schwarz G, Buchan K, Rivington M, Miller D. 2008. Wither agricultural DSS? *Comput. Electron. Agric.* 61:149–59
65. McCown RL. 2002. Locating agricultural decision support systems in the troubled past and sociotechnical complexity of "models for management." *Agric. Syst.* 74:11–25
66. McCown RL. 2002. Changing systems for supporting farmers' decisions: problems, paradigms, and prospects. *Agric. Syst.* 74:179–220
67. McCown RL, Carberry PS, Dalgliesh NP, Foale MA, Hochman Z. 2012. Farmers use intuition to reinvent analytic decision support for managing seasonal climatic variability. *Agric. Syst.* 106:33–45
68. McRoberts N, Franke AC. 2007. *A diffusion model for the adoption of agricultural innovations in structured adopting populations*. Work. Pap., Dep. Land Econ., Scott. Agric. Coll.
69. McRoberts N, Hall C, Madden LV, Hughes G. 2011. Perceptions of disease risk: from social construction of subjective judgments to rational decision making. *Phytopathology* 101:654–65
70. McRoberts N, Hughes G, Madden LV. 2007. Using the information entropy early in the design decision tools. *Proc. 2007 Eur. Fed. Inf. Technol. Agric. Food Environ., Glasgow*, July 2–5. Paris: ACTA Inform. **http://www.efita.net/apps/accesbase/dbsommaire.asp?d=6270&t=0&sid=57&idk=1**
71. McRoberts N, Hughes G, Savary S. 2003. Integrated approaches to understanding and control of diseases and pests of field crops. *Australas. Plant Pathol.* 32:167–80
72. Meade N, Islam T. 2006. Modeling and forecasting the diffusion of innovation: a 25 year review. *Int. J. Forecast.* 22:519–45
73. Mills WD, La Plante AA. 1951. Diseases and insects in the orchard. *Cornell Ext. Bull.* 711. 88 pp.
74. Miller PR, O'Brien M. 1952. Plant disease forecasting. *Bot. Rev.* 18:541–601
75. Mir SA, Quadri SMK. 2009. Decision support systems: concepts, progress and issues—a review. In *Sustainable Agriculture Reviews*, Vol 2, ed. E Lichtouse, pp. 373–99. Dordrecht: Springer. 992 pp.
76. Mumford JD, Norton GA. 1984. Economics of decision making in pest management. *Annu. Rev. Entomol.* 29:157–74
77. Murali NS, Secher BJM, Rydahl P, Andreasen FM. 1999. Application of information technology in plant protection in Denmark: from vision to reality. *Comput. Electron. Agric.* 22:109–15

78. Naranjo SE, Ellsworth PC. 2009. Fifty years of the integrated control concept: moving the model and implementation forward in Arizona. *Pest Manag. Sci.* 65:1267–86
79. Norton GA, Holt J, Mumford JD. 1993. Introduction to pest models. In *Decision Tools for Pest Management*, ed. GA Norton, JD Mumford, pp. 89–99. Cambridge: CABI. 279 pp.
80. Öhlmér B. 2001. Analytic and intuitive decision making: Swedish farmers' behaviour in strategic problem solving. *Proc. Conf. Eur. Fed. Inf. Technol. Agric. Food Environ., 3rd, Montpellier*, June 18–20, pp. 609–14. Montpellier: Agro Montpellier
81. Öhlmér B, Olson K, Brehmer B. 1998. Understanding farmers' decision making processes and improving managerial assistance. *Agric. Econ.* 18:273–90
82. Ojiambo PS, Holmes GJ, Britton W, Keever T, Adams ML, et al. 2011. Cucurbit downy mildew ipmPIPE: a next generation web-based interactive tool for disease management and extension outreach. *Plant Health Prog.* doi:10.1094/PHP-2011-0411-01-RV
83. Pethybridge SJ, Gent DH, Esker PD, Turechek WW, Hay FS, Nutter FW Jr. 2009. Site-specific risk factors for ray blight in Tasmanian pyrethrum fields. *Plant Dis.* 93:229–37
84. Pethybridge SJ, Hay FS, Esker PD, Gent DH, Wilson CR, Nutter FW Jr. 2008. Diseases of pyrethrum in Tasmania: challenges and prospects for management. *Plant Dis.* 92:1260–72
85. Pfender WF, Gent DH, Mahaffee WF. 2012. Sensitivity of disease management decision aids to temperature input errors associated with out-of-canopy and reduced time-resolution measurements. *Plant Dis.* 96:726–36
86. Pfender WF, Gent DH, Mahaffee WF, Coop LB, Fox AD. 2011. Decision aids for multiple-decision disease management as affected by weather input errors. *Phytopathology* 101:644–53
87. Puente M, Darnall N, Forkner RE. 2011. Assessing integrated pest management adoption: measurement problems and policy implications. *Environ. Manag.* 48:1013–23
88. Ridgley A-M, Brush SB. 1992. Social factors and selective technology adoption: the case of integrated pest management. *Hum. Org.* 51:367–78
89. Rodgers E. 2003. *Diffusion of Innovations.* New York: Free Press. 576 pp. 5th ed.
90. Rosenberger DA. 2003. Factors limiting IPM-compatibility of new disease control tactics for apples in eastern United States. *Plant Health Prog.* doi: 10.1094/PHP-2003-0826-01-RV
91. Rossing WAH, Heong KL. 1997. Opportunities for using systems approaches in pest management. *Field Crops Res.* 51:83–100
92. Rottenstreich Y, Hsee CK. 2001. Money, kisses, and electric shocks: on the affective psychology of risk. *Psychol. Sci.* 12:185–90
93. Royle DJ, Shaw MW. 1988. The costs and benefits of disease forecasting in farming practice. In *Control of Plant Diseases: Costs and Benefits*, ed. BC Clifford, E Lester, pp. 231–46. Oxford: Blackwell. 263 pp.
94. Schultz TW. 1939. Theory of the firm and farm management research. *J. Farm Econ.* 21:570–86
95. Secher BJM, Jørgensen LN, Murali NS, Boll PS. 1995. Field validation of a decision support system for the control of pests and diseases in cereals in Denmark. *Pestic. Sci.* 45:195–99
96. Shaw MW. 2002. Epidemic modelling and disease forecasting. In *Plant Pathologists' Pocketbook*, ed. JM Waller, JM Lenné, SJ Waller, pp. 252–65. Wallingford, UK: CABI. 528 pp. 3rd ed.
97. Sherman J. 2012. *"Farmers are the original ecologists:" contested meanings of sustainability in Pacific Northwest flavor crops.* Rural Sociol. Work. Pap., Dep. Sociol., Wash. State Univ.
98. Slovic P. 2000. *The Perception of Risk*. London: Earthscan Publ. 473 pp.
99. Smith TJ. 1996. A risk assessment model for fire blight of apple and pear. *Acta Hortic.* 411:97–104
100. Steiner PW. 1990. Predicting apple blossom infections by *Erwinia amylovora* using the MARYBLYT model. *Acta Hortic.* 273:139–48
101. Steiner PW, Lightner GW. 1996. *MARYBLYT* 4.3: *A Predictive Program for Forecasting Fire Blight Diseases in Apples and Pears*. College Park: Univ. Md.
102. Stern VM, Smith RF, van den Bosch R, Hagen KS. 1959. The integrated control concept. *Hilgardia* 29:81–101
103. Sultan F, Farley JU, Lehmann DR. 1990. A meta-analysis of applications of diffusion models. *J. Mark. Res.* 27:70–77
104. Sultan F, Farley JU, Lehmann DR. 1996. Reflections on "a meta-analysis of applications of diffusion models." *J. Mark. Res.* 33:247–49

105. Sunstein CR. 2003. Terrorism and probability neglect. *J. Risk Uncertain.* 26:121–36
106. Teng PS. 1985. A comparison of simulation approaches to epidemic modeling. *Annu. Rev. Phytopathol.* 23:351–79
107. Thomas CS, Skinner PW, Fox AD, Greer CA, Gubler WD. 2002. Utilization of GIS/GPS based information technology in commercial crop decision making in California, Washington, Oregon, Idaho, and Arizona. *J. Nematol.* 34:200–6
108. Thompson SV, Schroth MN, Moller WJ, Reil WO. 1982. A forecasting model for fire blight of pear. *Plant Dis.* 66:576–79
109. Trumble JT. 1998. IPM: overcoming conflicts in adoption. *Integr. Pest Manag. Rev.* 3:195–207
110. van den Bulte C, Stremersch S. 2004. Social contagion and income heterogeneity in new product diffusion: a meta-analytic test. *Mark. Sci.* 23:530–44
111. Venkatesh V, Bala H. 2008. Technology acceptance model 3 and a research agenda on interventions. *Decis. Sci.* 39:273–315
112. Volz E, Meyers LA. 2007. Susceptible-infected-recovered epidemics in dynamic contact networks. *Proc. R. Soc. B* 274:2925–34
113. Waggoner PE. 1968. Weather and the rise and fall of fungi. In *Biometerology*, ed. WP Lowry, pp. 45–66. Corvallis: Or. State Univ. Press. 171 pp.
114. Wang S, Krajbich I, Adolphs R, Tsuchiya N. 2012. The role of risk aversion in non-conscious decision making. *Front. Psychol.* 3:1–17
115. Way MJ, van Emden HF. 2000. Integrated pest management in practice: pathways towards successful application. *Crop Prot.* 19:81–103
116. Wearing CH. 1988. Evaluating the IPM implementation process. *Annu. Rev. Entomol.* 33:17–38
117. Willock J, Deary I, McGregor M, Sutherland A, Edwards-Jones G, et al. 1999. Farmers' attitudes, objectives, behaviours, and personality traits: the Edinburgh study of decision making on farms. *J. Vocat. Behav.* 54:5–36
118. Yuen JE, Hughes G. 2002. Bayesian analysis of plant disease prediction. *Plant Pathol.* 51:407–12
119. Zadoks JC. 1981. EPIPRE: a disease and pest management system for winter wheat developed in the Netherlands. *OEPP/EPPO Bull.* 11:365–69
120. Zadoks JC. 1984. A quarter century of disease warning, 1958–1983. *Plant Dis.* 68:352–55
121. Zadoks JC. 1988. EPIPRE, a computer-based decision support system for pest and disease control in wheat: its development and implementation in Europe. In *Plant Disease Epidemiology*, Vol. 2, ed. KJ Leonard, WE Fry, pp. 3–29. New York: McGraw-Hill. 377 pp.
122. Zalucki MP, Adamson D, Furlong MJ. 2009. The future of IPM: whither or wither? *Aust. J. Entomol.* 48:85–96

RELATED RESOURCES

1. Tait J. 1987. Rationality in pesticide use and the role of forecasting. In *Rational Pesticide Use*, ed. KJ Brent, RK Atkin, pp. 225–38. Cambridge: Cambridge Univ. Press. 360 pp.
2. Webster JPG. 1987. Decision theory and the economics of crop protection measures. In *Rational Pesticide Use*, ed. KJ Brent, RK Atkin, pp. 211–23. Cambridge: Cambridge Univ. Press. 360 pp.

Annual Review of Phytopathology

Volume 51, 2013

Contents

Errata

An online log of corrections to *Annual Review of Phytopathology* articles may be found at http://phyto.annualreviews.org/