Perceptions of Risk, Risk Aversion, and Barriers to Adoption of Decision Support Systems and IPM
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Perceptions of Disease Risk: From Social Construction of Subjective Judgments to Rational Decision Making

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ABSTRACT

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Many factors influence how people form risk perceptions. Farmers' perceptions of risk and levels of risk aversion impact on decision-making about such things as technology adoption and disease management practices. Irrespective of the underlying factors that affect risk perceptions, those perceptions can be summarized by variables capturing impact and uncertainty components of risk. We discuss a new framework that has the subjective probability of disease and the cost of decision errors as its central features, which might allow a better integration of social science and epidemiology, to the benefit of plant disease management. By focusing on the probability and cost (or impact) dimensions of risk, the framework integrates research from the social sciences, economics, decision theory, and epidemiology. In particular, we review some useful properties of expected regret and skill value, two measures of expected cost that are particularly useful in the evaluation of decision tools. We highlight decision-theoretic constraints on the usefulness of decision tools that may partly explain cases of failure of adoption. We extend this analysis by considering information-theoretic criteria that link model complexity and relative performance and which might explain why users reject forecasters that impose even moderate increases in the complexity of decision making despite improvements in performance or accept very simple decision tools that have relatively poor performance.

Plant disease management (PDM) involves the practical application of plant disease epidemiology. Because PDM involves human decision makers, as a subject for academic study, it is as much a social science as a natural science. However, the social science aspects of PDM have never been systematically developed and it is yet to become a truly interdisciplinary science.

One can usefully question whether the current version of PDM is working. It can be caricatured as a process in which plant disease epidemiologists continuously produce decision tools and disease forecasters, while repeatedly asking ourselves (collectively as a discipline, and in the face of many well-documented successes) why adoption rates for decision-tools are too low and why unwelcome barriers persist to more widespread adoption of the products of our efforts. One might further argue that if PDM was a truly interdisciplinary subject, involving social scientists, plant pathologists, and decision makers, a more fully rounded perspective of its aims and achievements would exist. This sketch should not be taken as a dismissal of the record of successful interaction between plant disease epidemiology and the social sciences, but obstacles to development of successful interdisciplinary research are well documented (27,30,36), and PDM is typical of many other areas which would benefit from better support for interdisciplinarity.

Fortunately, because both epidemiology and economics rely heavily on mathematical abstraction they can be combined relatively easily, improving the prospects for interdisciplinary exchange. The literature in this area dates from at least the late 1960s and 1970s (8–10,48) and has continued as a minor interest in epidemiology since (21,26,33,38,40,41,47,51). In this body of work, standard economic assumptions are made about decision makers' motivations and how they react to uncertainty among the possible outcomes from their decisions. That is, decision makers are assumed to seek to maximize profit or, more generally, utility (28) and that this single objective explains the choices they make. In responding to uncertainty, decision makers are assumed to conform to the theory of rational expectations. It is assumed that they use all of the available evidence to form expectations which are

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consistent with the long-term statistical outcome of repeatedly making the same decision; this allows for incorrect decisions in individual instances, but leads to long-term optimization (Box 1, section 4). Such economic, or decision-theoretic, approaches can be used in many effective ways to help in the design of decision tools. However, most of the applications of such techniques in PDM to date assume that the decision tools have already been

adopted and that the only risks that require analysis are those associated with disease outbreaks; the risks perceived by decision makers arising from lack of familiarity with new decision tools or disease management methods are often ignored. Our expectation as designers of decision tools and forecasters appears to be that if we demonstrate forecasters reduce risk, their adoption by growers will naturally follow. That adoption does not follow as often or as

BOX 1

A diagrammatic representation of the analytical framework for handling risk in the development of disease forecasters. The sections of the framework are described in detail in the corresponding sections of the paper. The key feature of the framework is a mechanism to allow formal integration of the impact and likelihood connotations of risk which are routinely identified in psychological and socio-economic analyses of risk into a decision-theoretic approach to building and evaluating decision tools.

widely as we continue to hope suggests that while our model decision makers may have rational expectations we do not.

In order to change this situation, a fuller analysis of how growers' perceptions of risks are produced and how they affect the adoption of new technology is required. As an added benefit the development of a broad, coherent, analysis of the relationships between risk, uncertainty, and decision tool adoption ought to stimulate a more interdisciplinary approach within PDM. The main aim of this paper is to lay out a possible framework that will allow PDM scientists to tackle the subject of decision tool development and adoption from a broad interdisciplinary perspective in the future.

WHAT IS RISK?

Risk has several definitions. Sometimes it can be usefully defined simply as the probability of an undesirable event. In the natural and physical sciences, risk often refers to the product of the probability of an event *and* its potential impact (37). By this definition risk is a probability-weighted cost, related to expected utility/regret in decision theory. This meaning of risk conflates the two separate, popular understandings of the word: the probability-likelihood-chance connotation, and the impact-cost-hazard-calamity connotation. In both popular and scientific use the two conno-

tations of risk can be used conjointly or independently leading to the possibility for confusion and ambiguity. In the social sciences, the definition of risk typically reflects the way the term is understood in common use and the process by which risk perceptions are formed is an important area of research. Such analyses reveal that risk itself does not provide a complete explanation of behavior under uncertainty; adoption of particular behaviors may depend on a wider set of factors. Two points arising from the preceding discussion form the central theme of this paper.

- Risk comprises uncertainty and potential impact. These elements may have independent or combined effects and both need to be considered.
- As an academic subject, PDM has been largely led by plant pathologists and epidemiologists who, understandably, have focused on the likelihood element of risks associated with disease and given much less attention to the impact element. If decision makers are more concerned with the impact element, then while both groups talk about "the risk of disease," they may well be referring to two different, but related, things. The adoption of decision tools or IPM approaches may increase if both likelihood and impact are given due attention during methodological development.

The remainder of the paper describes a framework for the development of decision tools in PDM that builds on these ideas. In

GLOSSARY

The summaries of terms given here reflect their meanings in this paper. Alternative and more formal definitions may occur in other contexts.

Risk: The concept of possible, but uncertain, harm which in both formal and informal definitions includes elements of the intensity or size of potential negative effects and/or the probability that such effects will be suffered.

Uncertainty: An element of risk, capturing the perception of potentially risky events as occurring somewhere on a range from definite to impossible.

Dread/hazard: An element of risk perceptions, capturing the perception of potential negative impact of risky events.

Social Constructivism: A body of sociological theory and research concerned with the extent to which individual beliefs and knowledge are constructed by social context and through social interaction.

Subjective probability: A concept of probability often associated with the Bayesian view of knowledge updating, which expresses an individual's strength of belief in a particular state of affairs. In keeping with other types of probability, subjective probabilities fall in the range from 0 to 1.

Psychometrics: A branch of psychology concerned with the quantitative measurement of psychological variables and the development of the theory underlying such measurements.

Utility: In economics and decision theory, utility is defined as the benefit or satisfaction obtained by an individual from a good or service. In many applications financial values are used as proxies for more complete definitions of utility.

Expected cost/expected regret: Continuing on from the definition of utility, costs, broadly defined, are losses of utility. Regret is the difference between the utility obtained from a decision made on imperfect information and the utility which would have been obtained had perfect information been available. Since the choice made was the best available the loss experienced cannot be avoided and therefore can only be regretted. For a set of mutually exclusive choices each with a specific cost/regret and probability of occurring, the expected cost/regret is the sum of all pairs of product of cost/regret and probability. For example suppose in a dice throwing game the cost associated with each face of a die is the value shown on the face. Given these assumptions, the expected cost of a single throw is

$$\left(\frac{1}{6} \times 1\right) + \left(\frac{1}{6} \times 2\right) + \left(\frac{1}{6} \times 3\right) + \left(\frac{1}{6} \times 4\right) + \left(\frac{1}{6} \times 5\right) + \left(\frac{1}{6} \times 6\right)$$

Skill value: A measure of the relative expected regret for one predictor/forecaster compared with a reference predictor. One approach to calculating skill value is to subtract the expected regret of the candidate forecaster from that of the reference and divide by the expected regret of the reference.

Naïve predictor/forecaster: A predictor or forecaster can be said to be naïve if it makes no direct use of evidence to differentiate the probabilities of different types of events in advance of their occurrence in particular cases where the associated expected cost is the simple probability-weighted sum of regrets (described above).

Akaike information criterion (AIC): The AIC is an information quantity which provides an estimate of the divergence between a reference data set and a test data set. It originates in information theory in which the data sets are typically probability density (or mass) functions, but it has a more generic interpretation as a measure of distance from truth, and is widely used as a combined model selection and goodness-of-fit statistic.

the next section we outline the framework, highlighting its main components. Five sections then deal in turn with the detail, preceding from the social construction of risk perceptions, to the role of probability, the formulation of expected costs (based on probabilities and impacts), and finally, the way in which information criteria might be used to assess users' resistance to adoption of new decision tools. The paper concludes with a brief discussion of future prospects.

A DESCRIPTION OF THE ANALYTICAL FRAMEWORK

The proposed framework has two aims.

- To provide a means for risks associated with plant disease to be analyzed in a systematic way in the process of design and

deployment of decision tools or innovative practices for PDM;

- To bring the analysis of barriers to adoption of decision tools within the process of designing and deploying such tools.

The framework is illustrated diagrammatically in Box 1, with important concepts in sections 3 and 4 shown in more detail in Box 2. It comprises five sections.

1. Users' risk perceptions are viewed as social constructions. Psychometric analyses and methods of discourse analysis can be used to determine which factors underlie uncertainty and impact components of risk for different user groups or adopters.
2. To deal with the fact that the likelihood (uncertainty) component of risk must encompass subjective and objective measures of uncertainty we introduce Mellor's (35) theory of indeterminate causation.

BOX 2

Relationships among the error cost ratio, β , probability for switching between rational disease control tactics, p^* , expected regret, $E(C)$, and skill value, K . For a given practical application, the basic forecasting problem is defined initially by the cost ratio. Starting from a known value of β , the tactical switching probability, p^* , for a simple naïve forecaster can be calculated (left panel) and is characterized by the pair of values (β, p^*) and is indicated by the large red point in each panel. The expected regret, $E(C)$, for the simple naïve forecaster, is calculated as a function of β and the probability of disease, p (lower right panel). The performance of one forecaster relative to another can be visualized by examining the skill value; the skill value is the difference in $E(C)$ between the two forecasters divided by the skill value of the reference forecaster (upper right panel).

3. Decision-theoretic approaches which combine the chance and impact elements of disease are introduced. Section 3 deals predominantly with the extent to which the error costs, which correspond to perceived hazards (or dread), can be used to construct rational, but naïve, forecasters which make no direct use of evidence about the actual probability of disease.
4. The fourth section introduces the performance of forecasters into the expected cost analysis and focuses on the uncertainty of disease. Expanding the analysis in section 3, we show that performance gains for decision tools may be relatively modest (in comparison with decisions that take account of the error cost ratio) when the cost ratio is small.
5. The final section of the framework considers what we refer to as *the adopter's dilemma*. This is the situation in which current decision making is known to be inadequate, but in adopting a proposed decision tool (or new behavior) the decision maker faces a trade-off between a promised, but uncertain, increase in decision quality and an increase in the complexity of his or her existing decision process. We use an analogy with the model selection/fitting problem in statistics (7,17) to illustrate how information criteria might be used to set targets for improvement in decision performance for new decision tools.

1. SOCIAL CONSTRUCTION OF RISK PERCEPTION

No single theory is likely to describe how perceptions of risk are formed. However, we contend that irrespective of how risk perceptions are created, they are amenable to being analyzed as functions of probabilities and costs in formal decision-theoretic and information-theoretic calculations. Thus, a major contribution that social sciences can bring to epidemiology is in analyzing the underlying factors that individuals and groups use in constructing their perceptions of the uncertainty and impact (or dread) aspects of risk perceptions. Social theorists (3,20) argue that individual perceptions of risk are socially constructed and depend on a wide range of factors (18,31). Theorists (3,4,20) and empiricists (16) emphasize the importance that the social context has in facilitating the mixing of factors which influence individuals' risk perceptions. Given this, risk perceptions will always contain a context- (or environment) specific component, and actual risk perceptions are therefore the result of individual-context interactions. To use terminology more familiar to epidemiologists, individual risk perceptions are a form of genotype-environment interaction. As epidemiologists we ought to be able to accommodate the idea that predicting individual perceptions of risk is difficult, while general patterns or trends are evident across a population. Despite the fact that the importance of the human element in epidemiology has been recognized for many years (52) and the demonstration that differences in farmers' practices can make profound differences to the functioning of production systems across wide geographic areas (42) little attention is routinely given to human behavior as a factor in epidemiology.

The psychometric analysis of risk perceptions is one approach which may be particularly easy to combine with existing epidemiological methods, and has the additional advantage that it has been widely used in studies of farmer decision making to examine farmers' attitudes, objectives, adoption of innovations and psychological attributes (1,2,33,49). In general, while farmers' attitudinal and personality traits show sample-scale correlations with differences in behavioral factors, such as likelihood to adopt new technology, accurately predicting individual behavior from underlying attitudes or personality traits is not very successful, corroborating the earlier point about the importance of individual-context interactions in these phenomena.

When used to examine risks specifically, psychometric analyses have shown that individual and aggregate data can be summarized

by two latent variables, or underlying risk dimensions, which correspond to independent perceptions of hazard (or "dread risk") and uncertainty (or "knowledge") (43). The hazard/dread variable captures individuals' perceptions of the size of potential negative impacts. The knowledge/uncertainty variable captures the extent to which lack of familiarity with potential hazards, and also the imminence with which the hazard might be experienced, influence the perception of risk. Dread (or potential impact) has been found to be more important than knowledge in determining overall perceptions of the combined perception of risk (43).

The two-way classification of risks into factors corresponding to chance and impact provides the mechanism for the transfer concepts from social research dealing with how risk perceptions are formed to the subsequent sections of the framework which utilize formal decision theory and information theory. Section 2 gives introduces an ontology for handling the different probabilistic measures of disease, which are entailed in decision-theoretic analyses of forecasters' capabilities.

2. THE PROBABILITIES IN DECISION THEORY

A more complete concept of probability would be useful to PDM in developing a decision-theoretic basis for evaluation of forecasters. Until now different metaphysical concepts of probability have been largely ignored in epidemiology (but not completely so, for example see Gold [21]). A brief introduction to some of the important issues in the metaphysical debate is given in Good (22). Since individual perceptions of the uncertainty of disease are subjective, and may differ from empirical estimates, having a clear mechanism for handling these different probability measures is important. The characterization of uncertainty outlined here is based on the Mellor's (35) treatment of causation and chance. The ontology contains three different ways in which uncertainty can be characterized: (i) the physical chances of events in the world; (ii) the observed frequencies of events, usually interpreted as objective probabilities which, in turn, can be interpreted as estimates of the underlying physical chances; and (iii) subjective beliefs, expressed as probabilities, in the values of the physical chances. All three of these quantities are probabilities in that they take numerical values bounded inclusively by 0 and 1 and obey the rules of probability calculus, including those in Bayesian updating (25). The notation for the quantities is as follows. The physical chance of an event, occurrence of disease, denoted $D+$ say, is $ch(D+)$, and may have some value, p ; $0 \leq p \leq 1$. Any collective of facts which have the property $ch(D+) = p$ will have the limiting frequency, $f_{\infty}(D+) = p$, in a series of independent trials in which $D+$ might or might not be true. Here, $f(\bullet)$ indicates a frequency, and the subscript infinity symbol (∞) denotes the paradigm case in which the frequency is estimated over an unboundedly large set of observations. The frequency of observed events in a finite set of n observations on $D+$, $f_n(D+)$, is interpreted as an estimate of p , $\hat{p}$. As in traditional statistical approaches, observed frequencies are considered to be objective probabilities. Finally, individuals' subjective beliefs that $ch(D+) = p$ are referred to as *credences* about $D+$ and denoted $cr(D+)$. Credences are identical to the subjective probabilities in Bayesian analysis (25). Mellor's (35) scheme has the advantage of separate notation for chances, frequencies and credences, allowing a clear differentiation of these different probability measures.

Mellor (35) notes that if our *only* evidence concerning event $D+$ is the knowledge that $ch(D+) = p$, then our rational $cr(D+)$ should also be p . Emphasizing the importance that credence (i.e., subjective probability) plays in decision making, Gold (21) argued that "In a decision problem, it is the subjective probability assignments of the DM [decision maker] that govern the decision. Given

that each decision situation is to a greater or lesser extent unique, frequency data are often not definitive, nor can the relevance of that data be decided objectively.” In contrast to this view, most of the development of decision theory in PDM has either implicitly or explicitly used frequency-based, objective estimates of a common prior probability of disease for all potential decision makers (32,47). That is, $f_n(D+)$ is taken as an objective prior probability for disease occurrence ignoring the fact that decision makers probably employ individual, and potentially different, values of $cr(D+)$.

The psychometric analysis of risk perceptions suggests that variation between individuals in credence of potential risks is significant (43), so future developments of decision tools or disease forecasters should assume a heterogeneity of credence assessments for disease problems in the intended user population. This heterogeneity has implications for the usefulness of decision tools and forecasters to different portions of the intended user-base (33). When such variation in credence is combined with estimates of costs for making incorrect decisions, as in the analyses outlined in the next section, one can begin to see that barriers to the uptake of decision tools exist simply because rational decisions can be made by many users, without forecasts. The interrelationships between uncertainty and error costs in specifying long-term per-

formance of forecasters is outlined in Box 2, which serves as a general point of reference for the next two sections of the framework.

3. EXPECTED COSTS: REGRET AND SKILL

The major emphasis in this section is on the extent to which considering error costs alone can improve decision making. We examine the effect that the cost ratio between “false positive” and “false negative” decisions has on expected regret. In keeping with the psychometric results, which suggest that individuals weight the dread (i.e., hazard, impact, or cost) aspects of risk more highly than the uncertainty aspects, we show that the error cost ratio has a large effect on expected regret compared with the simplest naïve assumption of equal error costs. This analysis illustrates two important issues. First, as the error cost ratio decreases, the overall expected regret decreases and the naïve tactic of always taking action has least expected regret over an increasingly wide range of values of $ch(D+)$ or $cr(D+)$. Second, as the cost ratio decreases, the prior probability at which any decision tool can have maximum benefit (compared with a naïve predictor) also decreases. This result has two further implications: (i) different types of forecaster may be required for situations with different

FIGURE 1

A, Graphs of relative expected regret against the probability of disease assuming different cost ratios (β) between false negative and false positive decisions. In all cases the false negative cost is scaled to equal 1. **B**, Graphs of skill value for comparing the four expected regret lines with cost ratios less than 1 against the expected regret line with cost ratio equal to 1. An explanation of the derivation of skill value is given in the text.

error cost ratios, and (ii) the prior credence of the subset potential adopters with largest potential gain from adoption also varies as a function of the cost ratio. This strengthens the need to tailor decision tools to specific situations in order to maximize the chances of adoption.

Consider a simple binary PDM decision problem in which the choices are either to use a fungicide if disease is predicted (D+) or to withhold treatment if no disease is predicted (D-). Suppose that in the absence of prediction, a decision maker's credence in the occurrence of disease is p ; i.e., $cr(D+) = p$ and correspondingly, $cr(D-) = 1 - p$. Further suppose that if disease does not occur, but the decision maker wrongly decides to apply the fungicide, the cost associated with this "false positive" decision is C_{FP} . There is an analogous "false negative" cost, C_{FN} , which will be suffered if the decision maker wrongly predicts D- in a situation in which D+ is true. These costs can be measured in financial values or more generally in terms of utility or regret (24,28). Over the long term the decision maker's expected regret, $E(C)$, can be calculated as shown in equation 1.

$$E(C) = \{(p \times C_{FN}) + [(1 - p) \times C_{FP}]\} \quad (1)$$

In equation 1 we make the simplifying assumption that correct decisions have no cost. Fabre et al. (14) and Pethybridge et al. (38) provide instructive examples where this simplifying assumption either is (38) or is not (14) included.

The expected costs of always treating or never treating are illustrated in the central panel of Box 1. Decision makers do not experience $E(C)$ at each individual decision point. Individual decisions are either right or wrong and result either in no regret if the right decision is made, or C_{FP} or C_{FN} , depending on which type of mistake has been made. Equation 1 characterizes the performance of a naïve forecaster (or predictor) in the long run; such forecasters are naïve in the sense that they do not use direct evidence for prediction and trust entirely to luck (5,13). In most situations in PDM, $C_{FN} \gg C_{FP}$. Subject to uncertainty about whether disease will occur, a naïve forecaster can use the difference in the error costs to implement a rational disease management strategy. The optimum naïve forecaster (ONF) strategy can be stated as follows.

- Obtain an estimate of the probability of disease, p , using either $p = cr(D+)$ or $p = f_{\infty}(D+)$ as appropriate.
- Calculate the expected regret for the tactics of treating ($E(C) = [(1 - p) \times C_{FP}]$) or not treating ($E(C) = p \times C_{FN}$).
- Choose whichever tactic has the lower value of $E(C)$.

When the $C_{FP} = C_{FN}$, the ONF results in a strategy in which treatment is withheld for $p^* \leq 0.5$ and is used if $p^* > 0.5$; the value $p^* = 0.5$ is the threshold probability of disease at which a rational switch in tactics occurs based solely on costs. We now denote the cost ratio, $C_{FP}/C_{FN} = \beta$. The threshold probability for switching between tactics occurs at a value of $p^* = \beta/(1 + \beta)$ and in situations where $\beta < 1$, $p^* < 0.5$. For $\beta \ll 1$ (corresponding to high crop values and relatively low treatment costs), p^* will be close to 0. This results in a rational strategy for almost all values of $cr(D+)$, in which the tactic with least $E(C)$ is to treat the crop without assessment of the current evidence of $ch(D+)$.

The effect of changing β on the expected regret is shown in Figure 1A. In Figure 1, regret is scaled for presentation purposes so that $C_{FN} = 1$, and $C_{FP} \leq 1$. The performance of the forecaster with $\beta = 1$ is indicated by the largest triangle in Figure 1A. We refer to this as the simple naïve forecaster (SNF) because it uses no direct evidence of disease and contains the simplest assumption about the cost ratio. The performance of the SNF serves as a benchmark against which all other potential forecasters can be measured. Naïve forecasters which have $\beta \neq 1$ will be denoted generically as ONF β , with β replaced by a numeric value to

identify specific examples. The remaining expected regret graphs in Figure 1 show the values of $E(C)$ arising from some naïve predictors, with $\beta < 1$. It is apparent that for small values of β the value of p^* approaches 0. The left graph in Box 2 shows the relationship between β and p^* for $0 \leq \beta \leq 1$.

Recently, Briggs and Zaretzki (5) extended the expected regret approach by introducing the concept of diagnostic or predictive "skill." The skill value, K , of a forecaster is a comparison of its expected regret with that of another forecaster. As indicated above, comparisons with the SNF serve as a universal benchmark. We denote the expected regret derived in equation 1 for $C_{FN} = C_{FP}$ as $E(C)_{SNF}$ to identify it as the expected regret associated with the SNF. Using similar annotation for the expected regret associated with ONF β , K is defined for the current situation by equation 2.

$$K = \{[E(C)_{SNF} - E(C)_{ONF\beta}]/E(C)_{SNF}\} \quad (2)$$

Plotting the values of K against p provides a simple way to evaluate ranges of p (i.e., $cr(D+)$) over which a forecaster will give better performance than the SNF. These ranges are as those for which $K > 0$. Figure 1B shows the skill value plots for the ONF β s in Figure 1A in comparison with the SNF.

Comparison of the skill plots in Figure 1B with the expected regret graphs in Figure 1A is of some interest. The simplest way to interpret Figure 1B is to examine the graphs of K as p increases from 0 to 1. None of the naïve forecasters have skill (i.e., values of $K > 0$), in comparison with the SNF, at values of $p \leq p^*$, because the expected regret for every naïve forecaster is $(p \times C_{FN})$ for $p \leq p^*$. However, for each ONF β , once its p^* is reached, $E(C)_{ONF\beta} < E(C)_{SNF}$ and the ONF β has skill (recall for each ONF β , $p^* = \beta/(1 + \beta)$). The skill values for the ONF β increase until $p = 0.5$ when the $E(C)_{SNF}$ begins to decrease; however, the ONF β always has skill in comparison with the SNF for $p > p^*$.

The preceding discussion shows that decision makers can do much to reduce long-term exposure to risk without adopting evidence-based forecasters, simply by taking account of the cost ratio for different types of decision error. The results captured in Figure 1 can be interpreted as a graphical exploration of the psychometric dread or hazard domain of risk from section 1 of the framework. In addition, Figure 1B shows the opportunity available to a forecaster to improve on the performance of ONF β in comparison with SNF. This opportunity is represented by the area of the skill graph to the left and above the values of ONF β . Clearly, for small values of β , there is little opportunity for a forecaster to provide more skill (relative to the SNF) than the ONF β . The same conclusion can be reached from the expected regret graph (Fig. 1A), where it can be seen that it is difficult for a forecaster to achieve lower expected regret than an ONF β with a small β . In principle, all of the information needed by individual decision makers to construct personalized expected regret graphs or skill value graphs, and devise rational strategies for disease management based on β alone, is available independent of evidence-based forecasters. For many decision makers such an analysis may be all the refinement to current decision-making processes that is needed or justified. It may also be possible to construct such analyses well in advance of the time when a decision is required since they use only the ratio of error costs and a value of $cr(D+)$. Bearing these comments in mind, in the next section we extend the analysis to include evidence-based forecasters in the framework.

4. ADDING THE PROBABILITY OF DISEASE: EVIDENCE-BASED FORECASTERS/PREDICTORS

If naïve forecasters relate to the dread or hazard dimension of risk, evidence-based forecasters, which are designed to make

accurate predictions of whether disease will occur or not, can be thought of as a means to address the uncertainty dimension. It is relatively simple to extend the analyses presented in Section 3 to include this information. Suppose we provide decision makers with a decision tool that is characterized by a false positive error rate, estimated from a typical case/control study (33,51) by its false positive proportion (FPP) and a negative error rate, estimated by its false negative proportion (FNP). The expected regret from using this predictor is found from equation 3.

$$E(C) = (p \times C_{FN} \times \text{FNP}) + [(1 - p) \times C_{FP} \times \text{FPP}] \quad (3)$$

Now the rational strategy for disease management will depend on whether, given a decision maker's $cr(D+)$, $E(C)$ is least for tactics that involve prediction, or those which simply depend on β . As indicated above, for small β , the range of values of p ($=cr(D+)$) over which prediction is a rational choice may be quite small, and limited to an interval which includes p^* ($=\beta/(1 + \beta)$). Hilden and Glasziou (24) and Drummond and Holt (13) provide graphical analyses of these points in medical and machine learning contexts, respectively.

In Figure 2, the example from Figure 1 is extended by including information from a prototype forecaster for prediction of Fusarium head blight (FHB) in wheat. The data underlying this

example were originally published by De Wolf et al. (12) and subsequently discussed in detail by Madden (32). Briefly, various potential weather-based forecasters for FHB were analyzed by De Wolf et al. (12), with the gold standard for classifying cases ($D+$) and controls ($D-$) provided by field sampling. For one of the forecasters tested, $\text{FPP} = 0.28$ and $\text{FNP} = 0.06$. Using reasonable estimates for wheat yields, yield losses arising from FHB, and treatment costs under Ohio growing conditions, with C_{FN} scaled to 1, $C_{FP} = 0.30$.

Figure 2A shows the expected regrets for the SNF (assuming $C_{FP} = C_{FN}$), the $\text{ONF}_{0.3}$ (with $\beta = 0.30$), and $\text{EBF}_{0.3}$, the evidence-based forecaster defined by the FPP, FNP, and $\beta = 0.30$, according to equation 3. Examining Figure 2A it can be seen that the optimum strategy over all values of p includes three different tactics. At low values of p , from 0 to p_1^* , the SNF has lowest regret. Between p_1^* and p_2^* , the $\text{EBF}_{0.3}$ has the lowest expected regret, and at values of $p > p_2^*$, the $\text{ONF}_{0.3}$ has the lowest expected regret. At values of $p > p_3^*$, the $\text{EBF}_{0.3}$ has higher expected regret than both the $\text{ONF}_{0.3}$ and SNF. The results based on expected regrets are mirrored by the corresponding interpretation based on skill values shown in Figure 2B. Here, the skill formula of Briggs and Zaretzki (5) for the $\text{EBF}_{0.3}$ is given as

$$K = \{[E(C)_{\text{ONF}\beta} - E(C)_{\text{EBF}\beta}]/E(C)_{\text{ONF}\beta}\}$$

FIGURE 2

A, Graphs of relative expected regret against probability of disease for the simple naïve forecaster (SNF), optimum naïve forecaster (ONF), and evidence-based forecaster (EBF) described for Fusarium head blight in the text of the paper. **B**, The skill value graphs for comparing the ONF and EBF against the SNF from Figure 1A. The dashed vertical lines crossing both plots indicate the threshold values (i.e., the probability of disease) at which the tactic with least expected regret and greatest skill changes. Explanations of the switches are given in the text.

In Figure 2B, it is apparent that $EBF_{0.3}$ has positive skill for disease probabilities between p_1^* and p_3^* , but the skill value for $ONF_{0.3}$ is greater than that for $EBF_{0.3}$ for values of $p \geq p_2^*$. In a practical setting, there are essentially two ways to consider these results. They can be interpreted in terms of their implications for individual decision makers, or they can be interpreted in terms of their implications for the value of forecasting to a population of users.

For individual decision makers the analyses provide a means to estimate a personal cost-benefit analysis for adoption of forecasting. In order to obtain that analysis, the decision maker must be able to provide an estimate of the probability of disease. As noted in section 2, for most decision makers this value will be $cr(D+)$, although decision makers who participate in crop management schemes run by either public or private extension services may operate with $f_n(D+)$ provided by the extension service. In either case, with an estimate of p (recall $p = \Pr(D+)$), the decision maker can calculate the expected regrets which are implied for using the $ONF\beta$ and the $EBF\beta$. The decision maker's estimate of the value of p places him or her at some location on the horizontal axis of the regret graph. A line projected vertically upwards from that position will intersect with the expected regret lines corresponding to the different disease management tactics. The decision maker should select the tactic corresponding to the lowest regret at his/her prior; the value of $E(C)$ (read from the vertical axis) at that position gives an indication of the long-run expected cost, relative to C_{FN} , of following that tactic.

One potential problem which decision makers face in using this approach is that the actual long run cost is not determined by their beliefs about the likelihood of disease, neither $cr(D+)$ nor $f_n(D)$, but by the physical chance, $ch(D+)$, of disease for their crops. If decision makers' beliefs about $ch(D+)$ (based on $cr(D+)$ or $f_n(D+)$) differ markedly from the true $ch(D+)$, then an analysis of expected regret will give misleading results. This is true whether decision makers examine the outcomes of their decisions against reality or not. In the absence of information that their decisions are leading to wrong, or suboptimal, outcomes decision makers are warranted to continue to hold their beliefs (34). This type of potential systematic suboptimal decision making is most likely to happen in situations where risk-averse growers have values of $cr(D+)$ much in excess of $ch(D+)$ and where C_{FP} is very low relative to crop value. In such situations routine application of unnecessary treatments is likely to go undetected by growers, who are warranted to maintain their $cr(D+)$ by the continuing result of satisfactory financial performance and the absence of evidence that better performance is possible. The presence of this type of issue within grower populations adds weight to the argument (Gent et al. (19) in this volume) that epidemiology, and PDM more widely, may need to adopt a more educational than prescriptive approach in order to bring about changes in farming practice.

In addition to analyses of the implications for individual growers, expected regret and skill value analyses allow epidemiologists the opportunity to examine the potential value of forecasters across a population of adopters with different $cr(D+)$. Returning to the example shown in Figure 2, it can be seen that the forecaster has something to offer growers for whom $cr(D+)$ (or $f_n(D+)$) is in the range from p_1^* to p_2^* ; approximately from $0.10 \leq p \leq 0.8$ (the values to 2 decimal places are $p_1^* = 0.08$, $p_2^* = 0.79$). Comparing the expected regret lines for the $ONF_{0.3}$ and $EBF_{0.3}$ in Figure 2A it is obvious that the largest difference between these forecasters occurs at the value of p corresponding to the tactical switching point from the SNF to the $ONF_{0.3}$. Across the population of growers, those with most to gain from $EBF_{0.3}$, in comparison with basing decisions purely on the error cost ratio, β , are those with $cr(D+)$ (or $f_n(D+)$) close to $p^* = \beta/(1 + \beta) = 0.23$. Based only on probabilities, growers in this range might be ex-

pected to avoid treatment since the odds of disease, odds($D+$), are $(0.23/(1 - 0.23)) = 0.30$ (to 2 decimal places), or informally, less than 1 in 3. However, because false negative decisions are more than three times as costly as false positive decisions, it is these growers that have the highest exposure to risk from disease, not those for whom disease is more certain. We see here again the point raised earlier that if efforts to improve PDM focus only on the likelihood of disease and ignore how likelihood interacts with cost, efforts may be wasted constructing forecasters with inappropriate operating characteristics, targeted at the wrong section of the population of potential adopters, or (in the worst case) which perform less well in the long run than tactics based only on the error costs. Making mistakes of any of these types in the development of forecasters is likely to result in tools that are poorly received by the intended user base and to correspondingly low adoption rates.

By examining the range of probabilities for which predictors have lower expected regret (or equivalently higher skill value) than naïve prediction, we can begin to characterize the conditions for probable adoption. Where current decision making is perceived by growers as inadequate, or where a clear advantage to adoption of forecasting can be demonstrated in principle, some incentive will exist for growers to adopt new approaches. However, adopting a new decision making process involves a trade-off between the additional complexity that decision tools may add to an existing decision problem and the additional benefits it might offer. One way to characterize this trade-off might be to use methods based on information criteria such as those used in statistical model selection (17), since the technology adoption problem facing growers has analogies with the statistical model selection/fitting problem. In the next section we outline how this approach might be formulated but attach the warning that the heuristic argument we present is work in progress, not the outcome of validated research.

5. INFORMATION CRITERIA AS GUIDES TO PREDICTING FORECASTER ADOPTION

It is a common scientific problem to select an appropriate type of model to describe a set of data and then to find the best-fitting model of the chosen type for the data. Historically, these two problems (i.e., model selection and model fitting) have been seen as separate, but within the last 15 years they have increasingly been unified through the use of information-theoretic approaches. The most widely used information criterion is the Akaike information criterion (AIC), but a range of similar diagnostic statistics is available (7,17).

A comprehensive introduction to the AIC is beyond the scope of this discussion, but the papers by Forster and Sober (17) and Burnham and Anderson (7) together give a wide-ranging account of its philosophical background, mathematical derivation, and practical application. The many references included in those papers contain a rich entry point to the literature in this area for interested readers to pursue. For our immediate purposes two points about the AIC are important.

The AIC is a measure of the expected relative entropy between two sets of data. The relative entropy is also known as the Kullback-Liebler divergence (or distance), D_{KL} (29), and is widely used in probability theory and statistics to measure the difference between probability distributions. D_{KL} is not strictly a distance metric because it is not symmetrical. It should always be reported with a clear indication of which distribution (or set of data) is serving as the reference distribution. Note that because it is widely used in the context of statistical modeling the AIC (and thus D_{KL}) is often viewed as the distance between observed data and a set of model predictions. In this context the data provide a

natural choice of common reference distribution. However, the AIC has a wider interpretation as the divergence between any pair of reference and test distributions. From an epistemological perspective, it can be viewed as a measure of divergence between the truth and any estimate of the truth (e.g., a set of empirical measurements or model predictions) (17).

In model selection/fitting, the “best” model is the one which has the lowest overall divergence from the truth (i.e., distance from the data). In classical statistics distance from the data is typically measured by the likelihood and model fitting is achieved by likelihood maximization algorithms (7). However, an arbitrarily complex model can be made exactly to reproduce a data set and hence achieve perfect likelihood, but we intuitively reject overly complex models as unrealistic. In order to be useful as a measure between a candidate model and the truth encapsulated in a set of data, the ability of the model to reproduce the data should be balanced against the model’s level of arbitrary complexity. The AIC (and similar information criteria) provides a quantitative measure of this trade-off. The AIC penalizes complex models by subtracting a value proportional to the number of estimated model parameters from the likelihood obtained from fitting the model to the data (7,17). Given a set of candidate models, the AIC essentially asks of each one, “Is your predictive power sufficiently good to justify the number of parameters you need?” Our suggestion is that the AIC could be employed in an analogous manner to set criteria for the construction of forecasters based on comparing their performance with preexisting decision schemes. A hypothetical example will illustrate the concept.

The AIC can be written in a number of different forms, but a useful one for the current purpose is shown in equation 4.

$$\text{AIC} = (1/N) \times (\log(L_f) - k) \quad (4)$$

In equation 4, N is the number of data points, $\log(L_f)$ is the log-likelihood obtained from fitting the model to the data and k is the number of estimated model parameters. In direct comparisons between competing models, the $(1/N)$ term is common to all estimated AIC values and can be dropped from the calculations. Readers should note that it is common for statistics programs to express AIC as $-2 \times (\log(L_f) - k)$, so that small numbers mean a good fit, but we do not follow this convention. Now consider the AIC in the context of forecaster adoption. In this situation, the “model” is the forecaster or decision tool and the data are observations of epidemics and nonepidemics. Suppose a situation in which a decision maker currently uses two parameters to decide whether to take action or not. For example, these could be crop development stage and date combined in a decision rule of the form:

If (crop development less than stage X) **and** (date later than Y)
then (treat)
else (do not treat)

Given the availability of a gold standard with which to verify the predictions made by the decision rule, its performance can be analyzed formally using a case/control experiment and log-likelihood calculated. Now suppose that the decision maker knows from experience that the decision rule is not very good. In the absence of a formal statistical analysis to arrive at this perception, a decision maker will use experience of correct and incorrect decisions to construct an informal estimate of the decision rule’s likelihood. Recent evidence from neurological experiments strongly suggests that some primate brains store relationships between uncertain evidence and predicted events in the form of statistical likelihoods (50), supporting our suggestion that a formal information-theoretic approach is appropriate as a framework for studying decision tool adoption as a competitive process among candidate models.

Suppose we recommend a new decision tool to the decision maker which retains the two existing parameters and adds two more; for example, some additional measures of weather conditions. The decision maker now has four parameters to incorporate into their prediction process, and the question arises as to whether the extra effort will be repaid in terms of improved predictive performance. Recall that faced with the choice between two competing models we should pick the one with the higher AIC value. Thus, we know that if the new model has more parameters than the existing one it must have a higher likelihood than the existing model to justify adoption, since if the likelihoods were equal the old model should be retained on the grounds of simplicity. We can use the AIC to specify a minimum value for the required increase in likelihood for the new model, given how many more parameters it involves than the old one. Writing L_{f2} for the likelihood of the new model (with 4 parameters) and L_{f1} for the existing model (with 2 parameters), the AIC for adopting the new model can be found by rearranging equation 4.

$$(\log(L_{f2}) - 4) > (\log(L_{f1}) - 2) \quad (5)$$

After some rearranging, the minimum AIC for this example is shown to be

$$L_{f2} > e^2 \times L_{f1} \quad (6)$$

The e^2 term arises from the fact that the new model in our example has two more parameters than the existing one; the general AIC is

$$L_{f2} > e^n \times L_{f1} \quad (7)$$

where n is the *difference* in the number of parameters between two competing models. This analysis poses a question to epidemiologists. If we want to give potential adopters a new decision model which involves them handling n new pieces of information (e.g., n new parameters or new rules in a risk algorithm), we can first ask ourselves whether the new model has a likelihood more than e^n times higher than the existing decision process. If the answer to that question is no, then perhaps it is an indication that a different approach is needed. In closing this extended conjecture, we note that the AIC, as an example of Occam’s Razor, can cut both ways. That is, if new decision models simplify the decision process by reducing the number of decision variables, they may be adopted despite worse performance than existing practices, if the gains in simplicity outweigh the loss of accuracy. Bad but simple might be a preferred option over good but complicated. Einstein’s well-known aphorism that models should be as simple as possible but no simpler is apposite here.

DISCUSSION

In this paper, we have outlined a possible framework that will allow the integration of approaches from various disciplines into the process of designing and evaluating decision tools. Our main focus has been on users’ perceptions of risk and how these can be included in the process. The motivation for this effort comes from the belief that the current approach in PDM is too narrowly focused on epidemiological issues and will continue to suffer from the perception of poor adoption unless a more interdisciplinary approach is taken. The results we have assembled within this framework suggest that a closer integration between epidemiologists, social scientists, and economists will lead to a broader understanding of the term risk in PDM, and to a richer set of analytical approaches becoming available for risk analysis. Until now, there has probably been an overemphasis on analyzing and

understanding uncertainty of disease at the expense of rigorous analysis of its impacts, and the effect that the cost ratio has on rational choices by decision makers.

The framework can be used to decompose the failure of adoption of decision tools or innovations into a number of different mechanisms through which the population of potential adopters (e.g., growers, crop consultants) is reduced to the set of actual adopters, and thereby to understand barriers to adoption. Thus, a complete analysis of the specification and potential demand for a new decision tool would include a progression through the analyses outlined at each stage of the framework, starting with an evaluation of the socioeconomic factors which underlie decision makers' perceptions of risk. This type of analysis would allow potential new decision tools to be embedded within an appropriate understanding of the context in which they will be used.

Linking social science and epidemiology will present familiar issues for interdisciplinary research. One way to facilitate successful collaboration between disciplines is to identify methodologies that bridge the gaps. One technique that may be useful in this respect, particularly since it is designed specifically to help in understanding subjectivity, is Q-methodology (44). The technique, which is essentially a data elicitation and structuring exercise followed by factor analysis, has been successfully used to study farmers' attitudes in a wide range of contexts (6,11,15,23). Fairly robust farmer typologies emerge from such studies and we anticipate that when applied to credences about disease risks, Q-method would be informative.

Further moves to embrace subjective probability measures are required in the formal methods suggested here for examining the expected costs of disease. McRoberts et al. (33) argue that using the standard frequency-based definition of probability as a measure of uncertainty in decision making, and basing expectations of decision maker's behavior on objective responses to such probabilities, does not provide an adequate explanation for observed failures of model or forecaster adoption. Sections 3, 4, and 5 in this paper lay out some of the ground which is open to exploration in further attempts to understand adoption processes in terms of credence and expected regret. Two areas of technical development which we foresee as being of particular importance are in (i) the further development of Mellor's (35) scheme for handling probability, and (ii) the wider use of information theory in unifying concepts in evaluation of forecasters. In particular, the concept of expected information gain (29,45) might be useful in addressing the issue of optimization for serially correlated decisions which is discussed by Pfender and Gent (39, this volume).

We have given a very broad introduction into some of the ways in which a closer collaboration between epidemiologists and social scientists might be expected to benefit PDM. It is likely that deployment of epidemiological information in disease forecasters and decision tools will continue to be the method of choice for epidemiologists to translate their research into a practical output. Concurring with the introductory paper to this symposium series (19), however, we believe that epidemiologists ought to give more attention to the pedagogic aspects of decision tools and forecasters and view the issue of behavioral change among growers from a more long-term perspective.

Improved dialogue between social scientists and epidemiologists and more use of analytical methods from the social sciences (particularly a renewed interest in decision theory among epidemiologists) are likely to reduce the on-going frustration within PDM over low adoption rates for decision tools and integrated disease management practices. If for no other reason, a better understanding of the intended user population of predictors among epidemiologists is likely to lead to better management of their expectations for adoption. We anticipate, in particular, that the current emphasis on decision-theoretic evaluation of fore-

casters is likely to lead to a renewed interest in forecasting among growers, as the performance of new forecasters is increasingly expressed in expected values (including impact of adoption) rather than predictive accuracy alone. Finally, we note that while the analyses initiated in this paper suggest considerable effort on the part of epidemiologists to change their research approach, there are also implications for funders and for our final customers, i.e., growers. Specifically, the framework outlined here is predicated on the idea that exposure to the risks associated with disease can be reduced in the long run by making appropriate use of available information. Two sorts of information needed to allow this to happen are generally in short supply. The first is high quality long-term data on disease intensities. Few data sets of sufficient length to allow robust long-run results to be estimated exist in the primary literature. If we are serious in our intent to understand the long-run interplay between disease dynamics and risks, a commitment to the cost of collecting such data is needed from funders. As Turchin (46) noted in the wider context of achieving a general understanding of ecological population dynamics, "If time-series data are not available, a systematic program for their collection should be initiated immediately."

A second component of the methodology which is often unavailable is information about counterfactual situations for treated crops to assess the result of not treating. This counterfactual information is needed for, among other things, the construction of gold standards (i.e., classifications of cases and controls). It is also required if risk-averse beliefs in the need for treatment are to be challenged with empirical evidence. In order for such information to be generated, a wider acceptance of its value among growers is needed. This requires innovators, who are prepared to challenge their own perceptions of risk, to get involved in the participative research process so that the next generation of decision tools is more fit for purpose than many of those which have been produced to date. Examples of such good practice in participative research already exist in the literature (38,47) and are available to encourage others to follow. We hope that epidemiology will learn from itself and prove that diffusion of innovations can be both rapid and comprehensive.

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