Integrating experience, evidence and expertise in the crop protection decision process

Hughes, G; Burnett, FJ

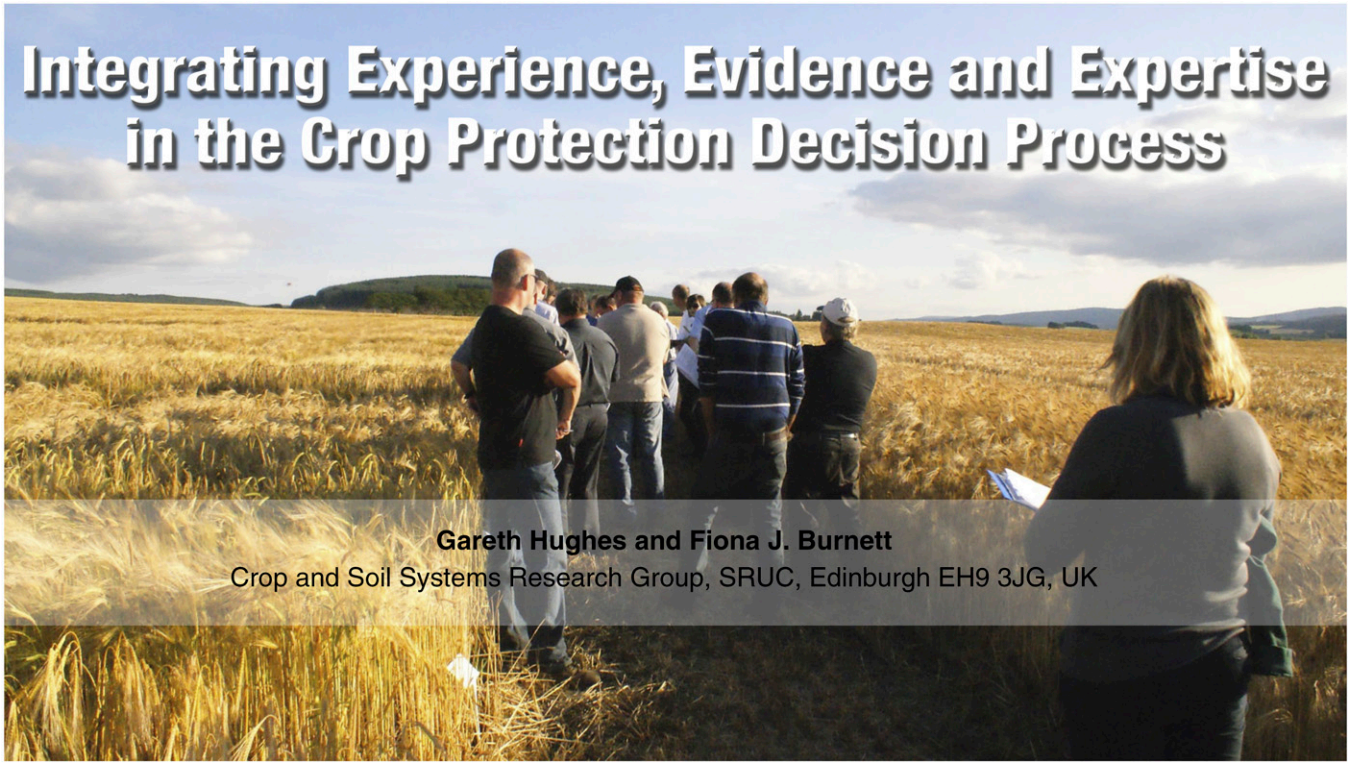
Published in:
Plant Disease

DOI:
10.1094/PDIS-02-15-0197-FE

First published: 01/01/2015

Document Version
Publisher's PDF, also known as Version of record

Integrating Experience, Evidence and Expertise in the Crop Protection Decision Process



Gareth Hughes and Fiona J. Burnett
Crop and Soil Systems Research Group, SRUC, Edinburgh EH9 3JG, UK

Effective crop protection depends on the quality of decision making in response to the threat of plant disease in much the same way that the quality of shared decision making by doctors and patients contributes to effective healthcare. This article delves into the clinical literature in order to provide a perspective on some recent discussions of shared decision making presented there, discussions that relate to issues also faced in sustainable crop protection. The aim in so doing is to contribute an overview of the decision process, looking in particular for a way in which decision owners (usually, in the context of crop protection at the field scale, the decision owners are the farmers) may have an opportunity to express their decision preferences. In the clinical situation, the diagnostic decision-making process involves a dynamic exchange between doctor and patient. A starting point is provided by Sbrojavacca (2012): "*When, as it happens often, we are in the grey zone of diagnostic uncertainty we use diagnostic tests to seek to reach a decision threshold*." ... "*Diagnostic tests are imperfect. In the grey area of diagnostic uncertainty they help us to reach a certain critical threshold beyond which we must decide*." From this perspective, diagnosis is more than identification. It is the requirement for treatment that is diagnosed, the aim of treatment being to prevent, or at least reduce, the extent of future adverse consequences. The term *diagnostic test* may refer to any procedure that provides evidence about factors related to those adverse consequences. Although diagnostic tests are imperfect, the application of diagnostic decision thresholds plays a fundamental part in the strategy of preventive medicine (Rose et al. 2008). Sbrojavacca describes an informal survey carried out among doctors taking part in training courses with the aim of eliciting a brief operative description of diagnosis. At least in part, it is Sbrojavacca's thought-provoking (and entertaining) account of his colleagues' survey responses that led us to consider our own perspective on the diagnostic process in crop protection decision making.

Unlike some of the respondents to Sbrojavacca's (2012) survey, Vickers et al. (2008) have no trouble defining clinical diagnosis: "*The concept of diagnosis is essentially binary*: *you either have a certain disease or you do not*." The authors then use this definition to draw attention to a problem they perceive that arises for diseases characterized by a continuous range of severity: categorizing individual patients either as having or not having the disease depends on a "*somewhat arbitrary cut-point*" of disease severity. Thus, from the perspective of Vickers et al., thresholds are (at least in some cases) regarded as an inadequate reflection of disease biology and invariable to patient preference. For example, Vickers et al. describe the diagnostic approach to blood pressure as a division of the population into two groups, those with hypertension and those without hypertension, and then treatment of the former group but not the latter. They propose instead that thinking about disease in terms of risk prediction is often superior to thinking about disease in terms of diagnosis. Here, *risk* refers to a probability associated with adverse consequences. In both clinical medicine and crop protection, the goal of diagnostic decision making is to facilitate risk reduction.

The essential idea in the approach of Vickers et al. (2008) is that a prediction model is used to estimate a patient's risk of a particular disease based on evidence related to risk factors, but that the result should not then simply be compared with a decision threshold for the purposes of diagnostic decision making. Vickers et al. suggest that the use of risk prediction models gives doctors explicit information (e.g., the risk of heart attack with or without treatment) to use in shared decision making with patients. This is a step in the direction of the patient as decision owner, although if the medical profession's grasp of the diagnostic process is as shaky as Sbrojavacca's (2012) survey seems to suggest, shared decision making between doctors and patients may not always be straightforward. And indeed, a recent report from a health literacy workshop led by the Royal College of General Practitioners (Rowlands et al. 2014) mentions that "*Written health literature and doctors' spoken communication are often not pitched at a level that is inclusive of people with low health literacy*." While that specific problem is far beyond the scope of the present article, it does serve,

Corresponding authors: G. Hughes and F. J. Burnett,
E-mails: gareth.hughes@sruc.ac.uk, fiona.burnett@sruc.ac.uk

Accepted for publication 12 March 2015.

http://dx.doi.org/10.1094/PDIS-02-15-0197-FE

at the outset, to emphasize the need for effective communication among all those involved in a decision process.

In his informal survey, Sbrojavacca (2012) asked doctors participating in training courses to provide—in a strictly anonymous fashion—a briefly written, operative description of diagnosis. We repeated this exercise for various groups of agriculturalists with an interest in crop protection, obtaining a total number of responses similar to Sbrojavacca's study. Each group was surveyed separately and was unaware of the other groups' responses. The results are shown in Figure 1. In presenting "word clouds" based on each group's responses, we hope that interested readers are stimulated to consider and evaluate their own personal response. Our initial impressions of the survey responses are as follows:

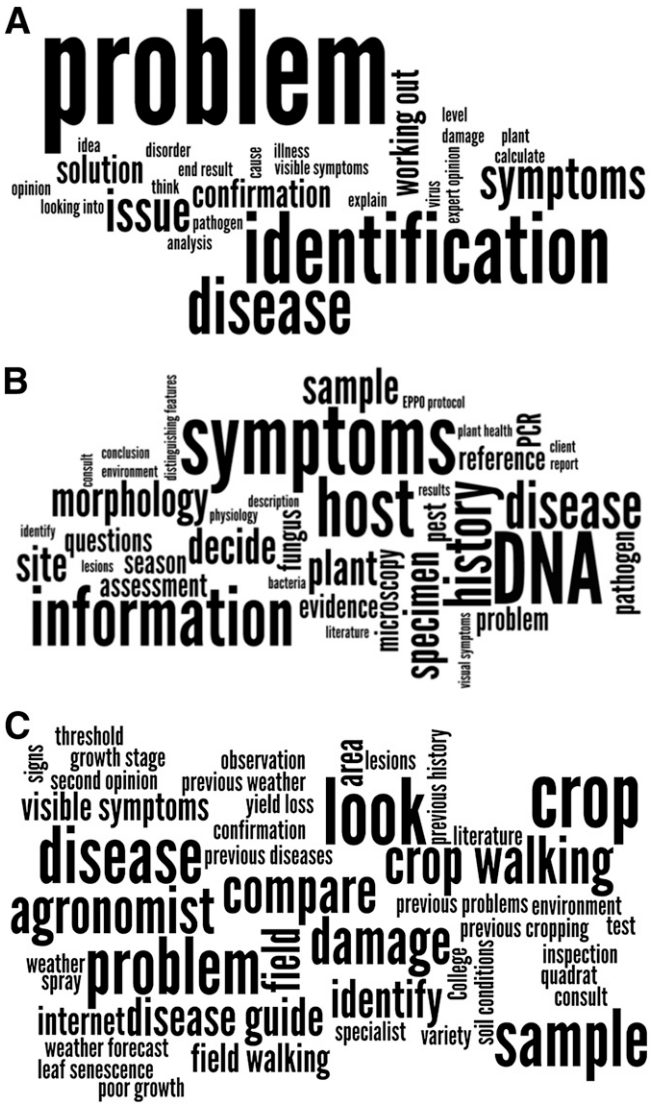


Fig. 1. Responses to an informal survey requesting a brief operative description of diagnosis from different groups of agriculturalists with an interest in crop protection, presented as "word clouds." The size of a word in the visualization is proportional to the number of times the word appears in the corresponding input text. The order of presentation (A, B, C) of the visualizations reflects the order in which the groups were surveyed, but groups were unaware of other groups' responses. The visualizations were prepared using Wordle (Jonathan Feinberg 2013, http://www.wordle.net/). **A,** A mixed group of trainee agronomists and farmers (sample size = 14) studying for the BASIS Certificate in Crop Protection (http://www.basis-reg.com/examsandtraining/courses.aspx?id=1. **B,** A meeting of the UK Plant Diagnosticians (UKPD) group, an informal network of scientists who run plant diagnostic clinics (sample size = 12). **C,** A class of Year 2 Agriculture students from SRUC (data set courtesy Dr. Graham McGrann, sample size = 18) (http://www.sruc.ac.uk/info/120409/agriculture).

- In terms of evidence from the crop in question, the survey responses mention a range of *signs* (indications of disease from direct observation of a *pathogen*: *microscopy*, *DNA*, *PCR*) and *symptoms* (indications of disease by reaction of the *host*: *visible symptoms*, *lesions*, *damage*, *poor growth*, *leaf senescence*). Other sources of evidence include current *host* data (*crop*, *variety*, *growth stage*), current *environment* data (*area*, *site*, *soil conditions*, *season*, *weather*), and some forecast data (*weather forecast*, *yield loss*).
- There is an overwhelming emphasis on obtaining objective evidence—data—as compared with subjective perceptions. But information may also be sought in the form of advice (*agronomist*, *consult*, *expert opinion*, *confirmation*, *College*).
- The methodology of evidence gathering receives attention, including both evidence gathered directly from a crop (*crop walking*, *field walking*, *look*, *observation*, *inspection*, *identification*, *assessment*, *description*, *sample*, *quadrat*), and evidence gathered from other sources (*literature*, *reference*, *internet*, *disease guide*).
- There is a place for information in the form of historical data (*previous history*, *previous problems*, *previous cropping*, *previous diseases*, *previous weather*).
- Our overall impression is that crop protection decision making is viewed by respondents as a *problem.* Diagnosis, which depends on the collection and assessment of *evidence* and *information*, is the corresponding problem-solving process.

But how does that problem-solving process work? Sackett et al. (1996), among the pioneers of modern evidence-based medicine, wrote, "*it's about integrating individual clinical expertise and the best external evidence*." Replace *clinical* with *crop protection*, and there is a basis to begin thinking about evidence-based crop protection. Reviewing the survey responses, but this time looking at diagnostic decision making through the lens of evidence-based crop protection, there is clearly a substantial appeal both to expertise and to external evidence. How may they be integrated?

Croskerry (2012) describes two pathways of diagnostic decision making, the *intuitive* (informal, subjective, context dependent, qualitative, dynamic, flexible) and the *rational* (formal, objective, scientific, quantitative, verifiable, rigorous). Integration of expertise and external evidence via the rational pathway leads to decision making that is less vulnerable to bias. Croskerry and Nimmo (2011) identify familiarity with the rules of probability and basic Bayesian probability theory among de-biasing strategies to reduce diagnostic error. Sbrojavacca (2012) writes "*Whether or not we like it, we behave, even unconsciously, like convinced Bayesians except that often we do not know how to draw the proper conclusions.*" That is to say, while decision makers recognize the need for integration of expertise and evidence in the diagnostic process, still they are prone to use the intuitive path rather than the rational path (Box 1).

It is interesting to note that none of Sbrojavacca's (2012) survey respondents mentioned any probability-based criteria in their descriptions of diagnosis. The same is true for our survey; many of the responses relate to adverse consequences, but not in probabilistic terms. There is no explicit mention of disease risk.

Now, thinking of crop protection decision making as a process involving the integration of expertise and evidence relating to disease risk, important epidemiological questions are:

- Where to start? (What is the initial disease risk?)
- What evidence to collect? (What are the relevant risk factors?)
- How to combine initial disease risk with evidence from relevant risk factors?
- How may the combined evidence lead to a decision?

In addition, we acknowledge that the farm-scale crop protection decision process is set in a wider societal context in which the range of responses to disease risk that are available to a decision owner may be subject to a variety of voluntary and/or legislative constraints. But first, in order to make an integrated assessment of evidence related to

disease risk at the farm scale, we adopt Bayes' rule as a principled method by means of which we may address the epidemiological questions above within a coherent framework (Box 2).

Essentially, in a diagnostic decision process, Bayes' rule provides a basis for updating the initial risk with evidence from risk factors relevant to the process. The application of Bayes' rule thus centers on the determination of the probability of need for a control intervention before (the prior probability) and after (the posterior probability) diagnosis. Madden (2006) calculates a detailed example from phytopathological data, and provides a technical glossary. For ease of cross reference, we adopt the same notation here.

Initial Disease Risk

The straightforward epidemiological approach is to adopt the epidemic prevalence of a disease in the population in question as the initial estimate of disease risk (i.e., the prior probability of need for a control intervention). However, this does not necessarily resolve the issue in relation to a particular decision problem. What is the appropriate population? Is enough known about the disease in question in that population to be able to assign a value to prevalence? Note that Bayes' rule does not tell us where the prior probability comes from, nor what the appropriate value is. These issues concerning specification of the prior have given rise to a great deal of discussion among statisticians, but it is not our purpose here to contribute to that debate.

Instead, let us assume that, after appropriate reflection, the population of interest can be identified (clearly, this is an issue requiring epidemiological expertise). Then the prior probability represents prior information about that population. If there is enough information to indicate with some level of certainty that the initial disease risk is low, then a low prior probability is appropriate. Similarly, if there is enough information to indicate with some level of certainty that the initial disease risk is high, then a high prior probability is appropriate. Intermediate prior probabilities reflect greater uncertainty (less information) relating to initial disease risk, with a prior probability of 0.5 representing maximum uncertainty. So information relating to epidemic prevalence will be reflected in the prior probability adopted as an initial estimate of risk for a population, and different priors reflect different levels of information. If the aspiration is evidence-based decision making, the goal should be that different participants in a decision process considering the same prior information should assign the same prior probability. It is in circumstances where the initial estimate of risk reflects a high level of uncertainty that there is most to gain from evidence-based decision making.

For application of Bayes' rule, some formatting of epidemiological quantities is required. The initial estimate of disease risk is denoted Prob(E+); i.e., the prior probability of the need for a control intervention. The corresponding prior probability of no need for a control intervention is denoted Prob(E−) such that Prob(E+) + Prob(E−) = 1. The prior odds of need for a control intervention is specified: odds(E+) = Prob(E+)/[1−Prob(E+)]. Similarly, if required, the prior odds of no need for a control intervention is: odds(E−) = Prob(E−)/[1−Prob(E−)] = 1/odds(E+). Then log[odds(E+)] and log[odds(E−)] may be calculated (the base of the logarithm can be chosen to suit the application; here, we use base-10 logarithms throughout).

Note that assigning a population value for the prior probability means that the circumstances relating to crop protection decision making for an individual crop based on the farmer's previous experience still remain to be taken into account in the decision process.

Selecting Risk Factors

A *risk factor* is a variable that serves as a predictor of the need for disease control intervention. Risk factors are thus the basis of diagnostic tests. Diagnostic tests based on risk factors are used to make predictions of the need for a control intervention in order to be able to make control interventions that are preventive. As in the clinical situation, the application of diagnostic decision thresholds plays an important part in this strategy (Box 3).

In their pioneering analysis, Stern et al. (1959) defined the economic threshold as the population density at which control measures should be used to prevent an increasing pest population from

Box 1. The intuitive statistician

This is a well-known example (see, e.g., Peterson and Beach 1967); but if you have not previously encountered it, try providing an answer here via your intuitive pathway (the answer calculated via the rational pathway will be given later). Two urns are each filled with a large number of colored balls. You know that one urn contains 70% red balls and 30% blue balls, and the other contains 70% blue balls and 30% red balls. One of the urns is then selected, but you do not know which. The selection was made on the basis of a fair toss of a fair coin (the outcome of which was hidden from you), so you may reasonably start by taking the probability of each urn being selected as equal to 0.5. To obtain evidence relevant to identification of the selected urn, you take a sample of balls from it (in such a way that you cannot select on the basis of color) as follows. The balls in the urn are thoroughly mixed and one ball randomly taken. Its color is then observed and recorded, and the ball replaced in the urn. The procedure is then repeated; after mixing, another ball is taken, observed, recorded and replaced. A sample comprising 8 red and 4 blue balls eventually results. What is the probability that the urn with mainly red balls was the one selected?

Box 2. Bayes' rule

We know from the monument in Bunhill Fields burial ground in central London that the Reverend Thomas Bayes FRS died on 7 April 1761 aged 59. So the year of Bayes' birth must have been 1701 or 1702; but at the time of writing the official record has still not been located. The work that describes what we refer to here as *Bayes' rule* was published posthumously, in 1764. An excellent narrative history of Bayes' work and its modern applications is now available (McGrayne 2011). In the present context, McGrayne's Chapter 4, *Bayes goes to war*, is where we begin. The use of Bayes' rule by Alan Turing and colleagues in their work on cryptography at Bletchley Park during World War II (Good 1979) began a renaissance for statistical applications of Bayesian methods in decision theory. In Bayes' rule, the codebreakers had a mathematical framework for analysis of probabilities that allowed quantification of the weight of evidence provided by individual clues in the available data, and a method of updating this quantity as further clues were revealed. Working in terms of logarithms meant that the updating of evidence was an additive process (Turing and colleagues used base-10 logarithms). Then, a prespecified decision rule was used to determine whether the evidence was sufficient to allow a judgment to be made. Much more recently, Van den Ende et al. (2007) adopted this approach in the context of diagnostic clinical epidemiology, presenting a diagrammatic approach to evidence accumulation that provides a useful visual representation of the Bayesian updating process (again using base-10 logarithms). A version of this diagrammatic approach could have application in crop protection decision making, where there is a natural time sequence of risk accumulation over the growing season.

reaching the economic injury level. The economic injury level is the lowest population density that will cause an amount of crop injury that justifies the cost of artificial control measures. This scheme recognizes that it is not a practical proposition to wait until a pest population reaches the economic injury level before taking action, and therefore that control measures should be taken in response to the threat of pest injury. Stern et al. were primarily concerned with the integrated control of arthropod pests, and in its original formulation, the economic threshold was denominated in units of pest population density. The range of crop protection problems under consideration here may involve a wider range of risk factors. In selecting a set of risk factors relevant to a particular crop protection decision process, a common-sense desire is to avoid possible double counting of evidence. In a diagnostic process based on several risk factors, Bayes' rule does not help us to identify risk factors, nor (at least in its simplest form of application) account for conditional dependence between them.

Identification and quantification of risk factors requires epidemiological expertise. Measures can be taken to counter the impact of conditional dependence, including careful selection of likely risk factors (remembering that the more that are used, the more that conditional dependence is likely to be a problem), and statistical assessment of dependence among factors. In cases where more than one risk factor is assessed during the course of diagnostic decision making, it is important is that the different sources of evidence can be assessed using a common currency. This is where Bayes' rule has its application.

Evidence Accumulation

We are concerned here with binary diagnostic tests. The basis for such a test is provided by placing a threshold on the measurement scale of a risk factor, such that crops that are scored above the threshold are predicted epidemics (requiring treatment, i.e., application of an appropriate product at an appropriate dose rate) and crops that are scored at or below the threshold are predicted non-epidemics (not requiring treatment). Note that risk factors are usually calibrated so that higher values correspond to greater need for intervention.

However, diagnostic tests, since they embody predictions, are imperfect. As described in Madden (2006), desirable properties for a good test are for Prob(P+|E+), the probability of a correct prediction of need for treatment, to be high (i.e., close to 1) and Prob(P+|E−), the probability of an incorrect prediction of need for treatment when there turns out to be no need for treatment, to be low (i.e., close to 0). These conditional probabilities are properties of a diagnostic test, estimated from data by, respectively, the proportion of epidemics correctly predicted (called the true positive proportion, abbreviated TPP, sometimes referred to as sensitivity) and the proportion of non-epidemics incorrectly predicted to be epidemics (called the false positive proportion, FPP). Similarly, for a good test, it is desirable for Prob(P−|E−), the probability of a correct prediction of no need for treatment, to be high (i.e., close to 1) and Prob(P−|E+), the probability of an incorrect prediction of no need for treatment when there turns out to be a need for treatment, to be low (i.e., close to 0). These conditional probabilities are estimated, respectively, by the proportion of non-epidemics correctly predicted (called the true negative proportion TNP, sometimes referred to as specificity) and the proportion of epidemics incorrectly predicted to be non-epidemics (called the false negative proportion FNP).

A binary diagnostic test based on a particular risk factor can be characterized by the likelihood ratio of a positive prediction (i.e., a prediction of an epidemic): LR(+) = TPP/FPP, and the likelihood ratio of a negative prediction (i.e., a prediction of a non-epidemic): LR(−) = FNP/TNP (e.g., Madden 2006). The likelihood ratio of a positive prediction tells us the extent to which a prediction of an epidemic (a positive result on the diagnostic test) is likely to come from an actual epidemic as compared with an actual non-epidemic (LR(+) should be a positive number greater than 1, the larger the value the better). The likelihood ratio of a negative prediction tells us the extent to which a prediction of a non-epidemic (a negative result on the test) is likely to come from an actual epidemic as compared with an actual non-epidemic (LR(−)

Box 3. Risk factors

The term *risk factor* originates with the systematic identification and quantification of behaviors (e.g., smoking) and biomarkers (e.g., cholesterol) associated with future coronary disease in The Framingham Study (Kannel et al. 1961). In the plant pathology literature an early use appears in Zadoks and Schein (1979), where the index includes a reference to *factors increasing risk*. The identification and quantification of disease risk factors has now become fundamental to modern epidemiology. In the context of decision making for crop protection, a useful way of thinking about risk factors relates to the generic *disease triangle* (D'Arcy et al. 2001), a diagram that shows the three important components necessary for disease: a susceptible host, a virulent pathogen, and a favorable environment. Risk factors are the particular host, pathogen, and environmental factors that increase disease risk in a given plant pathosystem. The generic disease triangle becomes a specific *risk triangle.*

Box 4. The rational statistician

Now we can return to the urn problem as set out previously for the intuitive statistician. Here, taking a Bayesian perspective, the objective is to calculate the probability that the urn with mainly red balls was the one selected, given the evidence from the sample. Under the conditions of the problem, the prior probability that the urn with mainly red balls was selected is equal to 0.5. Thus the prior odds is equal to 1 and the prior log-odds is zero. This is consistent with the situation in which you have no prior information that leads you toward a decision in favor of one urn or the other; at the outset, you are maximally uncertain. On the hypothesis is that the urn with mainly red balls was the one selected, TPP (the proportion of red balls in the urn with mainly red balls) = 0.7, FPP (the proportion of red balls in the urn with mainly blue balls) = 0.3, LR(+) = 2.333 and log[LR(+)] = 0.368. Also, FNP (the proportion of blue balls in the urn with mainly red balls) = 0.3, TNP (the proportion of blue balls in the urn with mainly blue balls) = 0.7, LR(−) = 0.429, and log[LR(−)] = −0.368. So the accumulated weight of evidence from the sample of 8 red balls and 4 blue balls is equal to $8 \times 0.368 + 4 \times (-0.368) = 4 \times 0.368 = 1.472$. Then the posterior log-odds in favor of the urn with mainly red balls being the one selected, given the evidence, is equal to the prior log-odds plus the weight of evidence: 0 + 1.472 = 1.472. To express this as a probability, first calculate the inverse log, $10^{1.472} = 29.641$; then the posterior probability that the urn with mainly red balls was selected, given the evidence, is equal to 29.641/(1 + 29.641) = 0.967. Peterson and Beach (1967) comment that most subjects who try this example typically provide an intuitive posterior probability of about 0.75, which is very conservative compared with the Bayesian posterior probability of 0.967. There is another way to look at this. The calculated posterior odds ≈30; but an intuitive posterior probability of 0.75 corresponds to an intuitive posterior odds of 0.75/(1 − 0.75) = 3, an order of magnitude smaller than the calculated value. Thus the example provides a simple illustration of the potential for bias on the intuitive decision path, because the intuitive decision path provides an unreliable assessment of the evidence.

should be a positive number less than 1, the smaller the value the better).

On taking logarithms, the resulting log[LR(+)] and log[LR(−)] are additive factors that describe the amount of evidence provided by the results of an imperfect binary diagnostic test. I. J. Good, who wrote extensively on Bayes' rule (after working with Turing during World War II on the analysis of the German naval cipher system) termed log[LR(+)] and log[LR(−)] *weights of evidence*. In the discussion of Good (1985), the following exchange is recorded:

> "*In short, my question to Professor Good is this one. What shall I do with weight of evidence?*"
>
> "*My answer is that the weight of evidence … should be added to the initial log-odds … to obtain the final log-odds.*"

Good's response is a statement of Bayes' rule, sometimes referred to as the evidence form of the rule. Stating Bayes' rule in this form provides, in essence, a bookkeeping procedure that allows us to keep track of evidence accumulation based on data relating to risk factors, by calculation of corresponding log-likelihood ratios (Box 4).

Among the desirable properties of log-likelihood ratios for evidence accumulation, we note the following.

- Log-likelihood ratios are independent of the prior probability; log[LR(+)] and log[LR(−)] are properties of a diagnostic test based on a particular risk factor.
- Log-likelihood ratios quantify evidence provided by the outcomes of diagnostic tests.
- Log-likelihood ratios provide a common currency for evidence accumulation. This is important because it allows us to accumulate evidence toward diagnostic decision-making using risk factors for which data may be recorded on different measurement scales. The unit of the common currency depends on the base of the logarithm used in calculation.
- Log-likelihood ratios are additive for a diagnostic process based on a series of risk factors (note that log-likelihood ratios are not probabilities, and that evidence is not accumulated additively on a probability scale).
- Expressing log-likelihood ratios as weights of evidence provides a terminology in which technical usage matches the everyday language interpretation.

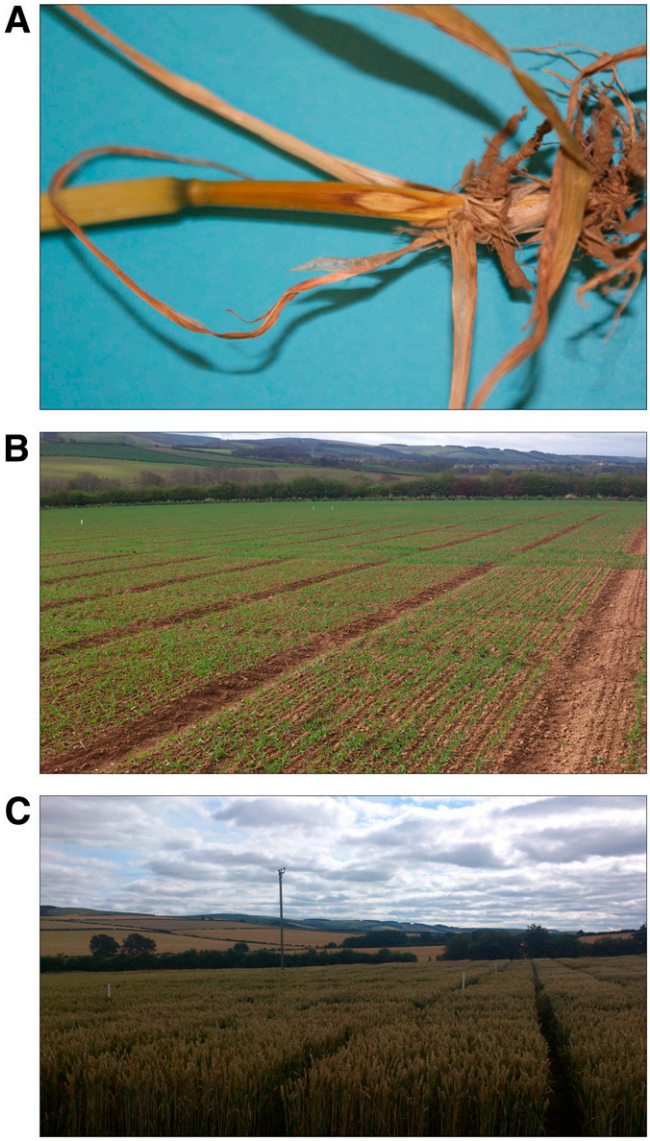


Fig. 2. Eyespot disease of wheat. **A,** Eyespot lesion on the stem base of wheat. **B and C,** Eyespot fungicide efficacy trials are part of the experimental program underpinning the new disease risk assessment. Trial plots are shown in the spring before assessment relating to the eyespot fungicide treatment decision (B) and later in the season after the treatment decision (C).

Reaching a Decision

Essentially what Bayes' rule provides is a formal structure for the problem of diagnostic decision making. The application of Bayes' rule enables the combination of an initial estimate of disease risk based on prior information with evidence related to disease risk in a current crop. It allows evidence from different kinds of risk factors, on different measurement scales, to be combined; leading to a risk prediction, the posterior probability of need for intervention given the evidence. Returning to Sbrojavacca (2012), where we started, he writes: "*What counts is that we are aware that the diagnostic process is based upon probability and not certainty, that we are prone to biases, those diagnostic tests can have false positives and false negatives, that having reached a certain threshold of probability and trust in diagnosis we should decide, with our patients, what to do or not do.*"

Box 5. The Fungicide Resistance Action Group UK (FRAG-UK)

FRAG-UK is a group of independent scientists and experts in fungicide resistance (Burnett 2011). It includes policy makers and representatives from industry, and produces messages on predicted resistance risk and on effective strategies to manage resistance risk. Farmers in the UK have lived with fungicide resistance issues almost since the introduction of fungicides to the UK market. FRAG-UK was established in response to these early resistance issues in order to bring together the collective experience of researchers, practitioners, and industry in an independent forum concentrating on issues affecting the UK. Farmers' attitudes to fungicide resistance have changed over the years, but it remains a challenge to promote resistance management strategies in a market that would put immediate crop yield and profit above product stewardship. Motivation to modify treatment preferences in order to improve stewardship and address the risk of resistance development requires clear messages about effective resistance management practices that are cognizant of the practical limitations of actual farming practice.

http://www.pesticides.gov.uk/guidance/industries/pesticides/advisory-groups/Resistance-Action-Groups/frag

Thus the Bayesian diagnostic process provides a rational path through probabilities and biases to a place where accumulated evidence is the basis for shared decision making. Shared decision making, as advocated by Vickers et al. (2008), might at first appear to have abandoned decision thresholds. But in the article's ensuing correspondence the point is made that regardless of whether binary diagnostic approach or a risk prediction approach is adopted, treatment of a patient still involves a threshold. The difference is that risk prediction allows the choice of operational threshold to be modified for the individual subject. Thus the risk prediction approach allows individual perceptions of risk to be taken into account, and therefore the patient's attitude to risk. The treatment of a patient still involves a binary decision, but the decision threshold has been individualized.

From a crop protection perspective, an example of a risk prediction approach is the management of eyespot disease of wheat (caused by *Oculimacula yallundae* and/or *O. acuformis*). In the United Kingdom, this is the most common and most damaging of the complex of diseases that infect the stem base (Fig. 2). A new risk assessment method—underpinned by continued fungicide efficacy trials—includes an early assessment of agronomic risks followed by a disease assessment carried out in Spring (GS30–31) to judge the need for fungicide application (Burnett and Hughes 2014). This enables farmers to identify individual fields at greater disease risk, allowing an integrated management approach through cultural control measures, such as the use of eyespot-resistant varieties and delayed sowing. This kind of risk prediction approach is consistent with a new study by Sherman and Gent (2014), who noted that: "*Respect for farmers' knowledge and experiences, recognition of their situation-dependent constraints and goals, and responsiveness to their individualized needs*" were valued factors contributing to decision making by farmers. However, farmers' individualized crop protection needs are part of a bigger picture.

The Bigger Picture: Collective Risk

In the clinical situation, for a risk-averse patient, effective treatment is a risk-reducing strategy since it prevents the undesirable outcome of foregoing treatment in the sick state (Felder and Mayrhofer 2014). But if the patient population is overwhelmingly risk averse, this can have consequences; for example, meeting widespread patient demand for antibiotics is at odds with strategies to limit increasing antibiotic resistance (Hawker et al. 2014). In farm-scale crop protection decision making, farmers, as decision owners, face similar issues. Crop protection decisions made on the basis of short-term disease risk at the level of the individual crop also have implications for long-term collective risk, for example in terms of fungicide resistance management. Indeed, there are notable similarities in the strategies for the management of fungicide and antibiotic resistance (van den Bosch and Gilligan 2008).

Control of fungal plant pathogens has been characterized by introduction of new fungicides and subsequent loss of efficacy with the emergence and selection of resistant pathogen genotypes (van den Bosch et al. 2011). Typically, farmers with crops to protect are risk averse, especially in the case of high-value intensive crops (Gent et al. 2011; Shtienberg 2013). In this context, the survey responses of grape growers in Oregon and Washington noted by Gent et al. (2013) are of particular interest. In a list of management considerations rated as "extremely important," *controlling pesticide resistance* ranked third, behind only *preventing major pest and disease outbreaks* and *treating diseases in early stages*. The issue then becomes one of managing actions in order to balance short-term individual risk and long-term collective risk.

Typically, decision making in crop protection depends on attitudes to risk and crop economics at the farm scale ahead of concerns about product stewardship. Farmers, post-diagnosis, may be able to select from a range of fungicides in a variety of tank mixtures, alternations, application timings, doses, and application equipment and technologies. If short-term predictions of economic gain are weighed against long-term predictions of the development of fungicide resistance, the impact of individual behavior may seem negligible when compared with the collective behavior of the population. Here, there is an important role for trusted independent sources of evidence; in the UK, the Fungicide Resistance Action Group UK (FRAG-UK) is one such (Box 5).

Voluntary stewardship will always be somewhat variable in implementation, so legislative restrictions may also be useful provided they are evidence based and do not overly limit productivity. For example, in the European Union, limitations on the permitted number of seasonal fungicide applications for products having a particular mode of action are often included in statutory advice on product labels and enforced through farm inspections, with breaches penalized through the system of Single Farm Payments. FRAG-UK has a role here in identifying those situations where resistance risks are of sufficient severity to merit such restrictions on use, and those where, on balance, voluntary stewardship would suffice. This kind of judgement of existing evidence is essential in an area where industry and regulatory decisions about fungicide resistance management are made in a dynamic farming sector (van den Bosch et al. 2014).

In Conclusion

A characteristic of agricultural policy problems is that governments, or other policy-making bodies, have only a limited set of variables under their direct control (Candler et al. 1981). At the policy scale, an issue for fungicide resistance management research is to provide farmers with the evidence base for operational integration of short-term crop protection decision making and longer-term stewardship measures. Further studies of farmers' risk perceptions and decision preferences in crop protection decision making can only help in the establishment of successful and sustainable programs that incorporate policy issues aimed beyond the farm scale. But it remains the case that measuring risk perceptions and decision preferences in a way that captures the effectiveness of an evidence-based approach to crop protection is problematic.

In the UK, some doctors have adopted *patient reported outcome measures* (PROMs) as a tool for eliciting patients' perceptions of the effectiveness of care (Black 2013). PROMs were initially developed for use in research, for assessing and comparing the outcomes achieved by healthcare providers, but the methodology can also serve to provide a database that has potential to help patients and doctors make better (shared) decisions. However, reading the views expressed in the published responses to Black's article only serves to emphasize the difficulties involved: for example, how can the same database both inform individual care and satisfy the requirements of audit, how can "*more protocols, red tape, targets and digital philosophy*" be justified in primary care, and how can PROMs do other than "*stoke the fires of bureaucracy*"?

The fact remains that while the effectiveness of shared decision making in an agricultural (or, as we have just seen, a clinical) setting may be extremely difficult to assess, finding ways to do so is a priority. And not just for research purposes, but because—as illustrated so well by Sherman and Gent (2014)—the quality of decision making depends ultimately on effective knowledge exchange among all those involved in a decision process. The integration of experience, evidence, and expertise is an aspiration that drives participatory approaches to the management of plant disease.

Acknowledgment

SRUC receives grant-in-aid from the Scottish Government.

Literature Cited

Black, N. 2013. Patient reported outcome measures could help transform healthcare. Br. Med. J. (Clin. Res. Ed.) 346:f167 [See also the responses to this article, available at http://www.bmj.com/content/346/bmj.f167/rapid-responses.]

Burnett, F. J. 2011. FRAG-UK (Fungicide Resistance Action Group – UK) – A review of the context, work and aims of this UK resistance action group. Outlooks Pest Manage. 22:62-63.

Burnett, F. J., and Hughes, G. 2014. Forecasting eyespot development and yield loss in winter wheat crops in order to guide management decisions. Outlooks Pest Manage. 25:4-6.

Candler, W., Fortuny-Amat, J., and McCarl, B. 1981. The potential role of multilevel programming in agricultural economics. Am. J. Agric. Econ. 63:521-531.
Croskerry, P. 2012. Perspectives on diagnostic failure and patient safety. Healthc. Q. 15:50-56.
Croskerry, P., and Nimmo, G. R. 2011. Better clinical decision making and reducing diagnostic error. J. R. Coll. Physicians Edinb. 41:155-162.
D'Arcy, C. J., Eastburn, D. M., and Schumann, G. L. 2001. Illustrated glossary of plant pathology. The Plant Health Instructor. Online.
Felder, S., and Mayrhofer, T. 2014. Risk preferences: consequences for test and treatment thresholds and optimal cutoffs. Med. Decis. Making 34:33-41.
Gent, D. H., De Wolf, E. D., and Pethybridge, S. J. 2011. Perceptions of risk, risk aversion, and barriers to adoption of decision support systems and integrated pest management: an introduction. Phytopathology 101:640-643.
Gent, D. H., Mahaffee, W. F., McRoberts, N., and Pfender, W. F. 2013. The use and role of predictive systems in disease management. Annu. Rev. Phytopathol. 51:267-289.
Good, I. J. 1979. Studies in the history of probability and statistics. XXXVII. A. M. Turing's statistical work in World War II. Biometrika 66:393-396.
Good, I. J. 1985. Weight of evidence: a brief survey. Pages 249-270 in: Bayesian Statistics 2. J. M. Bernardo, M. H. DeGroot, D. V. Lindley, and A. F. M. Smith, eds. Elsevier Science Publishers BV (North Holland), Amsterdam, The Netherlands.
Hawker, J. I., Smith, S., Smith, G. E., Morbey, R., Johnson, A. P., Fleming, D. M., Shallcross, L., and Hayward, A. C. 2014. Trends in antibiotic prescribing in primary care for clinical syndromes subject to national recommendations to reduce antibiotic resistance, UK 1995–2011: analysis of a large database of primary care consultations. J. Antimicrob. Chemother. 69:3423-3430.
Kannel, W. B., Dawber, T. R., Kagan, A., Revotskie, N., and Stokes, J., III. 1961. Factors of risk in the development of coronary heart disease – six-year follow-up experience. Ann. Intern. Med. 55:33-50.
Madden, L. V. 2006. Botanical epidemiology: some key advances and its continuing role in disease management. Eur. J. Plant Pathol. 115:3-23.
McGrayne, S. B. 2011. The Theory That Would Not Die. Yale University Press, New Haven, CT.
Peterson, C. R., and Beach, L. R. 1967. Man as an intuitive statistician. Psychol. Bull. 68:29-46.
Rose, G., Khaw, K.-T., and Marmot, M. 2008. Rose's Strategy of Preventive Medicine. Oxford University Press, Oxford, UK.
Rowlands, G., Protheroe, J., Price, H., Gann, B., and Rafi, I. 2014. Health Literacy. The Royal College of General Practitioners, London, UK.
Sackett, D. L., Rosenberg, W. M. C., Gray, J. A. M., Haynes, R. B., and Richardson, W. S. 1996. Evidence based medicine: what it is and what it isn't. Br. Med. J. (Clin. Res. Ed.) 312:71.
Sbrojavacca, R. 2012. "What, diagnosis?" Between Bayes and biases. Intern. Emerg. Med. 7:S173-S179.
Sherman, J., and Gent, D. H. 2014. Concepts of sustainablility, motivations for pest management approaches, and implications for communicating change. Plant Dis. 98:1024-1035.
Shtienberg, D. 2013. Will decision-support systems be widely used for the management of plant diseases? Annu. Rev. Phytopathol. 51:1-16.
Stern, V. M., Smith, R. M., van den Bosch, R., and Hagen, K. S. 1959. The integrated control concept. Hilgardia 29:81-99.
van den Bosch, F., and Gilligan, C. A. 2008. Models of fungicide resistance dynamics. Annu. Rev. Phytopathol. 46:123-147.
van den Bosch, F., Oliver, R., van den Berg, F., and Paveley, N. 2014. Governing principles can guide fungicide-resistance management tactics. Annu. Rev. Phytopathol. 52:175-195.
van den Bosch, F., Paveley, N., Shaw, M., Hobbelen, P., and Oliver, R. 2011. The dose rate debate: does the risk of fungicide resistance increase or decrease with dose? Plant Pathol. 60:597-606.
Van den Ende, J., Bisoffi, Z., Van Puymbroek, H., Van Gompel, A., Derese, A., Lynen, L., Moreira, J., and Janssen, P. A. J. 2007. Bridging the gap between clinical practice and diagnostic clinical epidemiology: pilot experiences with a didactic model based on a logarithmic scale. J. Eval. Clin. Pract. 13: 374-380.
Vickers, A. J., Basch, E., and Kattan, M. W. 2008. Against diagnosis. Ann. Intern. Med. 149:200-203 [See also the replies to this article and a response from the authors, Risk prediction versus diagnosis: preserving clinical nuance in a binary world. 2009. Ann. Intern. Med. 150:222–224.].
Zadoks, J. C., and Schein, R. D. 1979. Epidemiology and Plant Disease Management. Oxford University Press Inc., New York, NY.

Gareth Hughes

Gareth Hughes is Professor of Plant Disease Epidemiology in the Crop and Soil Systems Research Group at Scotland's Rural College (SRUC). Before joining SRUC in 2010, he had held faculty positions at the University of the West Indies and the University of Edinburgh. In 2000 he received the Lee M. Hutchins Award of the American Phytopathological Society (APS) and in 2003 he was made a Fellow of the Institute of Mathematics and its Applications. Professor Hughes' work includes *The Study of Plant Disease Epidemics* (co-authored with Laurence Madden and Frank van den Bosch, 2007) and *Applications of Information Theory to Epidemiology* (2012), both books published by APS Press. Analysis of the crop protection decision-making problem is at the center of Professor Hughes' research interests.

Fiona J. Burnett

Fiona Burnett is Professor of Applied Plant Pathology and Head of the Crop and Soil Systems Research Group at SRUC. Fiona is a key translational crop scientist in the UK and a high profile independent influencer of crop protection practices. She has dealt with contentious research themes, most notably pesticide usage—a heavily politicized topic in Europe and subject to intense media and stakeholder pressure. The steering groups and committees she contributes to are extensive and include the UK Plant Health Forum (Defra), the Scottish Government Stakeholders steering group for a Centre of Expertise in Plant Health and the British Crop Protection Councils Diseases Working Group. She chairs the Fungicide Resistance Action Group – UK and is in her second 3-year term of chairing the Association for Crop Protection in Northern Britain. She is also a Director of Scottish Quality Farm Assured Cereals Ltd.