SESSION 9A

FORECASTING, MODELLING AND RISK ASSESSMENT AS PART OF DECISION MAKING PROCESSES FOR PEST AND DISEASE MANAGEMENT

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Papers: 9A-1 to 9A-5

The application of decision theory in pest and disease management

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ABSTRACT
Forecasting, modelling, and risk assessment are all activities that take place as part of the decision-making process for pest and disease management. Decision theory integrates these activities, so providing a basis for formulating the characteristics of prediction systems and for assessing the usefulness of the predictions that we make by means of these systems.

"*We demand rigidly defined areas of doubt and uncertainty*!" Thus said an irate representative of the Amalgamated Union of Philosophers, Sages, Luminaries and Other Thinking Persons (Adams, 1979), nicely capturing the problem of prediction. We cannot make a decision without formulating some idea of what the future may hold (Drummond, 2001), but our idea of what the future may hold is subject to doubts and uncertainties that defy rigid definition. In order to make progress we must make judicious use of current best evidence. Clinicians who adopt this perspective on decision-making refer to the practice of 'evidence-based medicine' (Sackett *et al*., 1996; Ashby & Smith, 2000). The application of decision theory in pest and disease management is the basis for an evidence-based approach to crop protection.

Models used in pest and disease management are the result of attempts to identify and quantify the key risk factors influencing the spread of pest and pathogen populations in time and space. Decision theory provides a framework by means of which we can incorporate data on risk factors into evidence-based management of pests and diseases. For example, in the two-group case, we are faced with the choice between applying crop protection measures or withholding them. We must make this choice before we know for certain whether or not crop protection measures actually were required, because by the time we can measure economic crop losses, it is too late to prevent them. Thus, we need to make decisions based on predictions of their consequences. The purpose of a pest or disease management model is therefore to provide a prediction, or forecast, of the requirement for crop protection measures. In practice, predictors rarely, if ever, provide perfect discrimination. In addition to crops that are treated where intervention really was required (true positives) and those that were not treated where intervention really was not required (true negatives), there may be some decisions to treat crops that really did not require it (false positives), and some decisions not to treat crops that really did require it (false negatives). The rates of true positive decisions (sensitivity) and true negative decisions (specificity) characterize the accuracy of a predictor (Yuen *et al*., 1996). We can alter the sensitivity and specificity of a predictor by changing the operational threshold adopted for its use. For a predictor that generates a score positively correlated with the actual need for crop protection measures, the adoption of a low threshold score reduces false negative decisions, while the adoption of a high threshold reduces false positive decisions. The effects of different choices of threshold predictor score on the error rates for decisions can best be seen by means of a graphical plot of sensitivity against 1-specificity, referred to as a receiver operating characteristic (ROC) curve (Twengström *et al*., 1998).

Sensitivity and specificity are characteristics of the predictor. Sensitivity, for example, tells us the probability of a prediction of the need for crop protection measures, given that they actually were required. For practical decision-making, we need to be able to reverse the conditionality: that is, we wish to know the probability that crop protection measures are actually required, given a prediction of the need for crop protection measures. Bayes' theorem is the means by which this is achieved. Using Bayes' theorem, sensitivity and specificity are combined with information on the prior probability of the need for crop protection measures to calculate the posterior probability of the need for crop protection measures, given the evidence related to risk factors.

Generally, it is impractical to develop prediction systems for pests and diseases that occur very frequently or very infrequently. For infrequently occurring pests and diseases, the prior probability of need for crop protection measures is low, so a predictor with very high sensitivity and specificity would be required in order for a prediction of occurrence to increase the posterior probability of need for crop protection measures to a level at which action might be taken by a decision-maker. For frequently occurring pests and diseases, the prior probability of need for crop protection measures is high, so a predictor with very high sensitivity and specificity would be required in order for a prediction of non-occurrence to decrease the posterior probability of need for crop protection measures to a level at which action might not be taken by a decision-maker. Wider use of predictors might be expected for pests and diseases that are neither particularly infrequent nor frequent (Yuen & Hughes, 2002). In this situation, even predictors with relatively modest sensitivity and specificity attributes might be useful guides to decision-making in the practice of crop protection.

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Disease management decisions – making decisions that matter

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ABSTRACT

Rule-based systems for predicting the occurrence of pests have been proposed and used for over fifty years. More modern versions of these have been used in various computer-based implementations since the 1970s. It is often unclear how such systems are developed. In addition, objective methods for evaluating such systems are often lacking. This paper intends to present methods for evaluating such systems, and also describes statistical regression methods for the development of such rule-based systems.

INTRODUCTION

Plant protection decisions in agriculture, if they are to be applied on a case by case basis, need information about the occurrence of pests. This information needs to arrive in advance of the pest itself, and usually needs additional lead time in order for the control measures to be applied to the crop. For some diseases, it is not sufficient to wait for the appearance of disease symptoms, since these may appear too late for the control measure to be of any use. For fungal pathogens, where the control measure is (often) the application of fungicides, waiting for symptoms to appear may give the pathogen a head start that can be difficult, if not impossible, to retake. Protectant fungicides have little effect on the pathogen propagules that have already invaded the plant, though they may give protection against subsequent infections.

How easy is it for us to predict the future? If one looks far back in history, our ancestors looked to changes in natural phenomena to see if they could see what the future might hold. Even today, there are people that use tea leaves or tarot cards to have a glimpse into the future.

Systems that use the action of birds, how tortoise shells crack when heated, or tea leaves are usually not used to predict the occurrence of plant diseases. As scientists, we are equipped with additional information that we can use to help us predict when a particular disease will affect a crop. This is information that we use automatically when giving advice regarding the occurrence of disease. For example, assume that cabbage is planted in a field. If that field had been planted with cabbage the year before, and that the cabbage in that field was severely affected with club root, most of us could then use that information to predict that the cabbage planted this year would also have club root. It is because of our knowledge of the life-cycle of the pathogen (*Plasmodiophora brassicae*) that enables us to make this prediction.

In making these predictions, we use our knowledge of the biology of pathogen. Sometimes the biology is complicated so that predictions need to be based on several pieces of information. In the club root example, the mere fact that cabbage was planted the year before is not sufficient to make a prediction about club-root. It is the fact the cabbage was affected by club root that is important. The number of years between the previous cabbage crop and this one is also of some importance, although the pathogen is long-lived and can also survive on some weeds.

The mere existence of a predictive system (or even it's use) does not necessarily mean it is good, correct, or of any use. Take an example of eyespot of wheat in Sweden. An information sheet on plant protection was published in Sweden (Olvång, 1992) and discussed some of the factors that might affect disease development, based on knowledge of the biology of the pathogen, *Pseudocercosporella herpotrichoides* (the asexual stage of *Tapesia yallundae*). The author went as far as to assign various numbers of points to factors such as foliage density, weather, previous crop, straw residues, weeds, and cultivar of wheat (Table 1).

While the author himself stated that the table was of limited use in predicting the use of fungicides, this did not hinder the ministry of agriculture in Sweden from requiring the use of this table for farmers who applied for subsidies related to 'environmentally friendly conventional agriculture'.

Table 1. Risk factors that affect development of eyespot in wheat (Olvång, 1992). These were also used by the Swedish ministry of agriculture in a quantitative manner for steering application of fungicides.

Canopy	Sparse, poorly developed	0
	Normal	++
	Dense, luxuriant	++++
	Dense, very luxuriant	++++++
Spring weather	Dry	0
	Normal	+
	Wet	+++
	Very wet	+++++
Previous crop	Winter wheat, rye, triticale	+++
	Winter or spring barley, spring wheat	+
	other	0
Straw residues (on soil surface	slight	0
after winter wheat, rye or triticale	abundant	++
Ground covering weeds	slight	0
(chickweed, Veronica sp.)	abundant	++
Variety	Solid/Kosack	0
	Holme/Hildur/Helge	+
	Folke/rye/Triticale	+++

Is the scheme efficient or not? Does the use of this scheme aid farmers to reduce the use of pesticides, or to reduce the risk of eyespot damage? One method of assessing this is to select some wheat fields, examine the amount of eyespot damage (in the absence of fungicide application) and to calculate the number of points that the table would have generated. If the scheme is efficient, we should see more points in those fields that had higher levels of eyespot.

In other words, there should be some correlation between eyespot and the number of points. A graph of the number of infected plants in the spring, and the number of points from the scheme, however, indicate that the predictor is of little use (Figure 1). One would think that there is a better way.

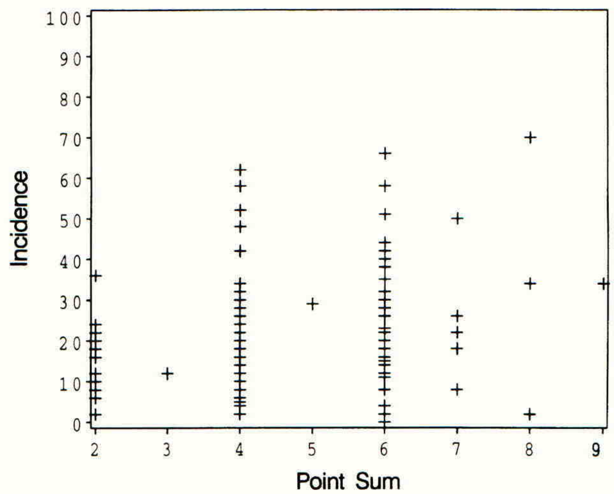

Figure 1. Eyespot incidence in the spring and the sum of points using the table 1 from wheat fields in Sweden from 1987 and 1988.

IDEAS AND TERMINOLOGY

Evaluating Prediction Systems

One important factor to consider in predictive systems is how often they give incorrect predictions. Although many process-based epidemiological models use amount of disease as the final output, farmers are usually faced with making yes-no decisions (Bernoulli variables) that entail the use of pesticides or not. In this context, errors and correct decisions can be summarized in a 2 x 2 table, using methods borrowed from (human) clinical epidemiology (Yuen *et al*, 1996).

Table 2. Definition of true and false positive rates based on recommendations and actual outcomes

	Disease Present	Disease Absent
Spray	A	B
Don't Spray	C	D
Total	A+C	B+D
	A/(A+C) True Positive	B/(B+D) False Positive

The proportion of correct predictions when the pest is actually present is called the sensitivity. Likewise, the proportion of correct decisions when the pest is absent is called the specificity.

Predictive schemes often have a continuous (or almost continuous) variable as an output. This can result from various point schemes (such as the eyespot example). In this case, varying the cutoff level where the control measures are to be applied (referred to here as the decision threshold) can affect both sensitivity and specificity.

Refer again to Table 1, where increasing numbers of points are given to factors that favour disease development. A lower decision threshold will, in general, cause more fields to receive fungicides. This can raise the sensitivity of the predictor, but also decrease the specificity. A decision threshold of zero, for example, will lead to all fields being sprayed. Such a predictor has high sensitivity (i.e. all fields that need a spray receive one) but poor specificity (i.e. all fields that don't require pesticides also receive them).

The opposite situation occurs with an extremely high decision threshold. If this is so high that no fields receive a spray, then the specificity is good (we haven't sprayed those fields that didn't need one) but sensitivity is poor (fields that needed a spray are missed).

By varying the decision threshold, a range of values for sensitivity and specificity can be obtained of these. A plot of these (often the x-axis is 1-specificity, also called the false negative rate) is referred to as a receiver operating characteristic (ROC) curve (Metz, 1978). Various theoretical curves are presented in Figure 2. The predictor A is the best, B is a little worse, and C has no predictive value at all.

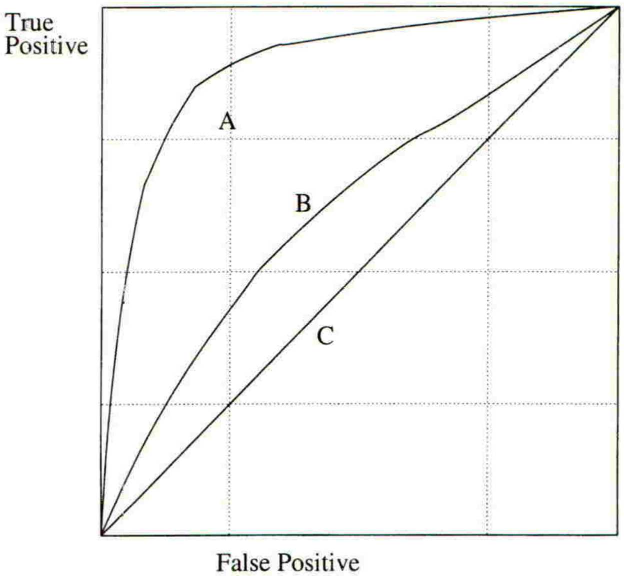

Figure 2. Theoretical ROC curves, ranked from best (A) to worst (C)

A ROC curve from the initial eyespot data presented in the introduction (with 30% disease severity as the economic threshold) is not shown but resembles predictor C in the Figure 2. One can argue that this is a poor outcome (incidence at DC 30 is a poor predictor for disease later) but the data set lacks sufficient number of observations late in the growing season to use eyespot incidence at a later date as the final outcome. The poor performance of the predictor, however, was not unexpected given the poor correlation between disease and the point sum (Figure 1).

A ROC curve provides a rapid, easy to use method of presenting a predictive system. The sensitivity and specificity that is coupled with a specific decision threshold can be easily read from the graph, and the graphical presentation allows comparison of systems that have completely different scales.

Development of Prediction Systems

The origin of many rule-based systems is not always clear. The development of the apple scab rules by Mills was not a simple task, and contained much revision and adjustment (MacHardy & Gadoury, 1989). While much biological information must be used in the development of rules in this manner, there is also much subjective judgment that may (or may not) be justified.

The need to apply pesticides (or not) was considered a Bernoulli variable in the previous section. This leads to a classification problem, where we would like to ascertain the characteristics that will enable us to distinguish the fields that require pesticides from those that do not. Two statistical procedures that can be used for this type of classification problem are the discriminant function and logistic regression. While the discriminant function is more efficient in separating two groups, it requires more stringent assumptions (multivariate normality of the explanatory variables) than logistic regression. In the absence of such conditions, logistic regression provides a robust method for separating two groups, and even performs reasonably well with multivariate normal populations (Press & Wilson, 1978).

Logistic regression calculates the logarithm of the predicted odds of the outcome (in our case the odds of pest:no pest) as a function of the explanatory variables. These can be both categorical variables or continuous variables. Logistic regression falls within the family of *general linear models*, a concept which unites it with other types of models such as analysis of variance (ANOVA), multiple regression, Poisson regression, and probit analysis (McCullagh & Nelder, 1989). One drawback to logistic regression is that the estimation of the regression parameters cannot be performed analytically, and that numerical methods have to be used to perform the regression. Given the performance and cost of modern computers, this is not a major drawback.

Logistic regression allows us to validate a set of predictive rules if we have access to a suitable data set. Analysis of the eyespot data used to present Figure 1 was less than promising. Of the variables that were available in the data set, none was able to predict the need to apply fungicides for eyespot. The information needed for this kind of prediction was not available in this data set.

One study conducted in Sweden was able to validate a predictor for Sclerotinia stem rot with a large data set using logistic regression (Yuen *et al*., 1996). It was found that some variables could be eliminated, and that new point values could be assigned to the remaining variables. If one examines the original point table (Table 3) proposed by Twengström & Sigvald (1993), one can wonder just why the difference between no infection and low infection in the last crop (equal to 10 points) gave the same change in risk as the difference between more than normal rain and normal rain in June (also equal to 10 points). By examining all of these factors together in a regression model, one can determine which variables are confounded with others and which ones are unnecessary. Confounding of variables can take place in two ways. In one way (rain in June and rain the last two weeks) the variables represent almost the same information, and one can be eliminated if the other one is present. In another type of confounding, one variable must be present for the other variable to have explanatory value. The number of years since the last oilseed crop is an example of this, which is only important if level of infection is also included. Some variables (such as the one concerning peas) have no explanatory value alone or in combination with the others.

A statistical analysis of different decision rules can do more than just eliminate unnecessary variables. The linear predictor resulting from the analysis represents the logarithm of the predicted odds of disease occurrence. Thus, the regression coefficients from the analysis can be used to adjust the points assigned to the different answers.

A comparison of the recalibrated rules with the original set using ROC curves indicated that the new rules performed as well, or better than the original. The new rules are not perfect, however, and still leave room for the errors that were mentioned above.

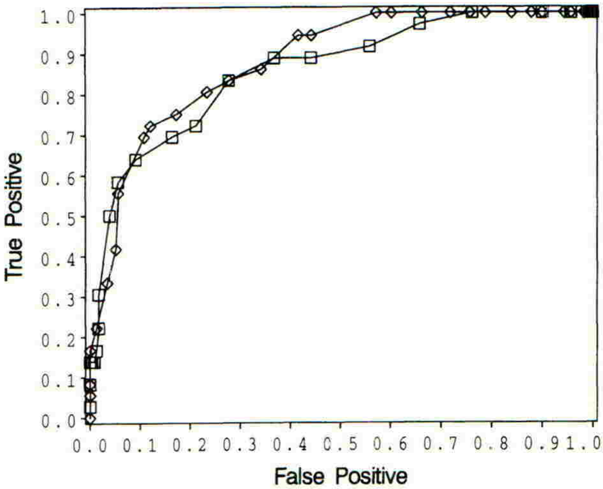

Figure 3. Receiver operator characteristic curves from the original disease forecast algorithm for Sclerotinia stem rot (—□—) and the recalibrated algorithm after logistic regression (—◇—).

CONCLUSION

Rule-based decision support systems can be a valuable component in modern agricultural production. As a minimum requirement, the possibility for errors in these systems should be acknowledged, and the performance of the rules documented with sensitivity and specificity. Knowing the performance of a system will enable the targeting of areas where there is a chance that it might be used. The use of ROC curves allows presentation of sensitivity and specificity even with varying decision thresholds, and is also a method of comparing risk algorithms that do not have the same scale. An added advantage is that it allows for flexibility on the part of the decision maker. Variable decision thresholds, with varying TP and FP rates, can reflect the different risk attitudes. A risk averse decision maker may spray his fields with a lower 'point

Table 3. Risk factors for sclerotinia stem rot prediction with points from original prediction algorithm

Risk factor	Possible Answers	Points
Number of years since last oilseed crop	more than 6 years	0
	5-6 years	5
	3-4 years	15
	1-2 years	20
Level of infection in last oilseed crop	None	0
	Low (1-10%)	10
	Moderate (11-30%)	20
	High (31-100%)	30
	Don't know (low risk)	10
	Don't know (high risk)	20
Have peas been grown in the field during the last five years	No	0
	Yes	5
Foliage density (including weeds) 0.5 m above ground	Thin	0
	Normal	15
	Heavy	30
Rain in June	Less than normal	0
	Normal (35-55 mm)	10
	More than normal	20
Rain the last two weeks	Less than 10 mm	0
	10-30 mm	15
	More than 30 mm	25
Weather forecast	High pressure	0
	Variable	5
	Low pressure	10
Regional risk value for apothecia development (per 100 sclerotia)	0-5	0
	6-10	5
	11-20	15
	21-100	25

accumulation', when compared to a decision maker more willing to take risks. He could thereby increase his sensitivity, but at the cost of decreasing the specificity. The advantage of the ROC curves is that the rate of both kinds of errors can be estimated. Given these error rates and the relative costs of both kinds of error, the decision maker can determine a critical value for his decision threshold, that reflects his attitudes toward risk. Sensitivity and specificity are also required for a Bayesian analysis of the predictive system (Yuen & Hughes, 2002).

Logistic regression provides a way of verifying, calibrating, and even developing decision rules if data sets of sufficient size and resolution are available. The importance of different factors that affect disease can be evaluated in a systematic manner, and the relationships between these different factors quantified. Unnecessary factors can be eliminated. Although the linear relationship among the explanatory variables seems to imply an additive relationship, this is related to the logarithm of the odds of disease occurring, and thus assumes a multiplicative relationship between the factors. The logistic regression approach is more robust when compared to discriminant analysis, though it may be less efficient.

Documentation of the performance of decision rules regarding pest control and pesticide application is an important step if they are to become a part of modern agricultural production.

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Towards an early warning system for winter wheat disease severity

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ABSTRACT

A new approach towards data mining algorithms was developed to predict *Septoria tritici* on winter wheat (cv. Riband) using meteorological data. Using binary data, we derived a qualitative model predicting the presence or absence of disease (at a 5% severity level) from weather data before GS 33 (temperature from January until early March and windspeed from late April until early May). Above the decided level, we used a linear regression to predict severity at GS 75 from rainfall data during stem extension. In order to validate the algorithm, we also derived a test statistic using bootstrap analyses.

INTRODUCTION

Severe losses of yield and quality can result from poor disease control. As a consequence, there is a tendency for crop managers to be very risk averse. However, as most crops do not get most diseases in most seasons (Hardwick *et al.*, 2001), this strategy leads to over-use of fungicides and a reduction in margin for the grower.
Because weather is often a very important factor in the spread of plant pathogens, many models (mechanistic and statistical) have been developed in the past to predict disease severity using meteorological variables (Rouzet & Murer, 1988; Shtienberg, 1991). However, such models are often seen as complicated and unreliable and have rarely been used in practice to aid disease management. Farmers generally prefer to rely on "rules of thumb" to decide the appropriate fungicide dose.

Coakley *et al.* (1982) developed an algorithm to explore the relationship between weather variables and disease, based on data mining. The algorithm has been used to derive predictive models for diseases of wheat and rice. For example, Hansen *et al.* (1994), Coakley *et al.*(1985) and Parker *et al.* (1999) worked on *Septoria tritici* and Coakley *et al.*(1982) analysed yellow rust. Although the algorithm has often been criticized as potentially unreliable (Shaw, 2002), no detailed work investigating this assertion has ever been published. We therefore generalized the algorithm and tested its validity using bootstrap analyses. To improve the original version of the program, we developed a two-step analysis to allow the construction of predictions that are qualitative ("Will an epidemic happen?") and quantitative ("How much disease would there be if the crop were left untreated?"). We used this approach to predict *Septoria tritici* on winter wheat in England.

"WINDOW PANE" EARLY DEVELOPMENT AND PREVIOUS USES

Coakley *et al.* (1982) developed an iterative algorithm (Window Pane) to relate weather to winter wheat disease severity. At the same time, a similar approach was developed in horticulture by Goldwin (1982) and was then used in entomology (Thomas *et al.*, 1983; Rispe *et al.*, 1998). In the Window Pane algorithm, correlations between disease and a number of weather "functions" (e.g. mean, number of days when a given weather variable is above a threshold, etc…) are calculated for different "windows". These windows are defined by a starting date and a window length (Figure 1). For every weather function analyzed, the window of highest absolute correlation with disease is found ("*optimum window*"). The functions with the largest correlations with disease are then combined within a multiple linear regression to derive predictive models of disease severity. The algorithm used by Goldwin (1982), although based on an iterative search like Window Pane, was more restrictive than the latter and only allowed mean values as weather functions.

Over the past 20 years, Window Pane has been used to derive predictive models of various diseases such as yellow rust (Coakley *et al.*, 1988) and *Septoria tritici* (Coakley *et al.*, 1985; Hansen *et al.*, 1994; Parker *et al.*, 1999) on winter wheat. Coakley *et al.* (1985) used a restricted disease data set (12 years at one site) and measured disease severity over the whole crop. They derived a model from Window Pane by deriving a very large number of weather functions (e.g. the "total consecutive days with temperature less than or equal to 7° C") from three weather variables (rain, minimum and maximum temperature). In their work, Hansen *et al.* (1994) pooled together data from the two *Septoria* species (*Septoria tritici* and *Septoria nodorum*) at 197 localities during 10 years. Severity was measured as a percentage green leaf area over the whole plant. When using Window Pane, they restricted themselves to weather functions derived from rainfall. In 1999, Parker *et al.* (1999) reported an analysis done on 20 observations of *Septoria tritici* at GS 73/75 on leaf layer 2. In this work, they logit-transformed the disease data before reporting the weather "functions" found to be highly related to disease severity.

Both Goldwin's "*correlogram*" (Rispe *et al.*, 1998) and Window Pane rely on the same iterative search for large correlations. This has often been seen as the main weakness of the method and it has been argued that such a screening method would *almost always* lead to high correlations because of the large number of variables and windows tested (Shaw, 2002). It may therefore appear surprising that this problem has never been addressed in the past and that the validity of the correlations reported in the cited work mentioned above has not been tested and/or reported. Although Coakley *et al.* (1985) presented a number of test and validation criteria, these were only concerned with the selection of the sub-models and did not test the weather variables selected by the algorithm. Many other studies using Window Pane have also relied on observations of p-values to test the significance of the correlations found despite the inapplicability of the p-value for repeated tests on the same data. When he first introduced his "*correlogram*", Goldwin (1982) mentioned the issue of iterativity and recommended the use of cross-validation or of new independent data sets to validate the model, but did not give any method to assess the validity of a given correlation before having derived the model. In more recent work, Rispe *et al.* (1998) used Monte Carlo simulation to overcome the inadequacy of p-values to test the significance of the highest correlations they found. In order to reduce the risk of considering spurious correlations, Thomas *et al.* (1983)

and Hansen *et al.* (1994) chose to restrict their analysis to time periods likely to be of importance *a priori*. This approach is questionable for two main reasons. First, it makes it harder, if not impossible to suspect any dubious or "by chance" correlation as their validity might not be tested very hard because of their *a priori* biological meaning. Second, this approach is very restrictive as no unexpected correlation will ever be found.

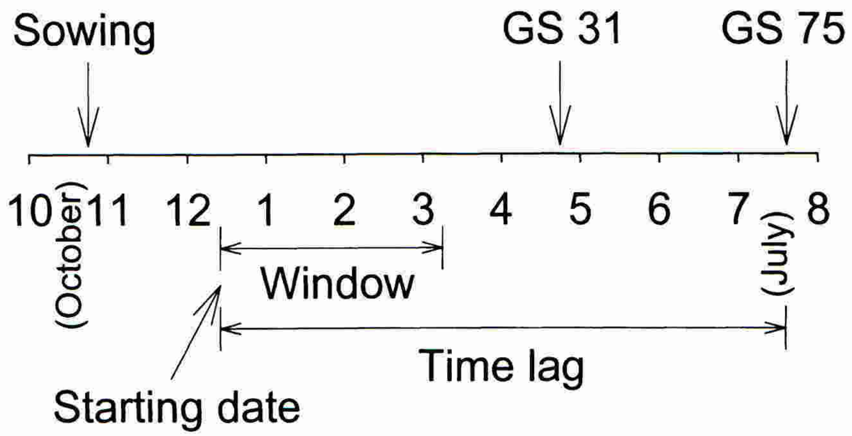

Figure 1. Example of a window with its starting date late November and a window length of 70 days.

AN IMPROVED VERSION OF WINDOW PANE

In our modified version of the initial Window Pane algorithm, we first addressed the problem mentioned above caused by the iterative nature of the program. We developed a test statistic, based on the number *N* of "consecutive" (e.g. starting on January 5th, 10th and 15th) windows with a "significant" correlation. Using a bootstrap technique, we showed (Pietravalle *et al.*, unpublished data) that a careful study of the *N* statistic allows better differentiation of "likely genuine correlations" from "likely spurious correlations".

All previous analyses based on the Window Pane algorithm have considered disease severity scored on a continuous scale between 0 and 100%. However, disease is relatively rare, so observations taken from crops are commonly skewed towards low disease severity. This can cause problems when modelling, because the cluster of points corresponding to low observed severities inappropriately increases the number of degrees of freedom of the regression and may lead to an artificially good fit. We therefore improved the original algorithm by allowing disease severity to be classified using a binary scale and using the proportion of observations which could be correctly classified using the value of a weather function as a measure to replace correlation. In our analysis, we used data of *Septoria tritici* on winter wheat (cv. Riband) collected during four years (1993/94 until 1996/97) at nine sites throughout England. From there, we developed a "two-step process" (Figure 2). First, sites were scored "0" (absence of disease) if severity was lower than 5% over the top three leaf layers at GS 75 or "1" (presence of disease) otherwise. In order to ease the use of the program, we redefine the windows using a "time lag" to define the starting date (Figure 1). We used our generalized version of the algorithm with misclassifications to find weather variables initiating the epidemic. Those variables were subsequently combined with a discriminant analysis to derive a discriminant function (Eq. 1) allowing qualitative prediction of severe *Septoria tritici* at GS 75.

A site is classified as "non-diseased" if:

$$h(x) = 2.7\, Wind_{Avg}\,[78,25] + 0.41\, T\min_{Nod;7}\,[190,70] - 33.7 > 0 \qquad \text{Eq. (1)}$$

where $Wind_{Avg}$ represents the average wind speed throughout the window and $Tmin_{Nod;7}$ is the number of days during the window when the minimum temperature is less than 7 °C. The time lag (number of days before GS 75) and window length are shown in the square brackets.

In a second step, a correlation approach using actual severity estimates was used, but restricted to sites where the epidemic was present at a 5% threshold at GS 75 (i.e. severity greater than 5% over the top three leaf layers). After optimizing the window for the largest correlation, a linear regression was obtained to derive a quantitative estimate of *Septoria tritici* at GS 75 (Eq. 2).

$$S_{GS_{75}} = 13.8\,(1.5)\, Rain_{Nod;9}\,[90;37] + 6.1\,(2.8) \quad \text{Adj. } R^2 = 86\% \quad \text{Eq. (2)}$$

where $Rain_{NOD;9}$ is the number of days in the window when more than 9 mm rain fell. The time lag and window length are shown in square brackets and the standard errors are between round brackets.

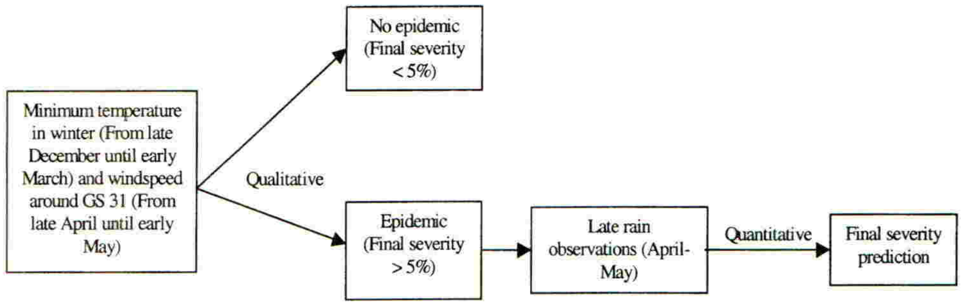

Figure 2. Two-step process prediction of *Septoria tritici*. First, a qualitative model was derived to predict the presence or absence of disease and, if *Septoria tritici* is present (at a 5% severity over the top three leaf layers), a quantitative model gives a prediction of the actual severity of *Septoria tritici* on the top three leaf layers at GS 75 if the field is left untreated.

DISCUSSION

Previous studies that used data mining techniques such as Window Pane never its validity and based their results on observations of p-values. Such analyses are limited in their value because of the autocorrelation of some weather variables (e.g. temperature) , the complexity of such data mining techniques and the need for a better test for the selection of weather variables. One large correlation between disease severity and weather is likely to be due to infection events occuring over a long time-period. On the contrary, even if spurious correlations will still occur, because of the autocorrelation of weather variables, these will be on a much smaller range. Therefore, the *number of significant correlations in time lags around the optimum window* was chosen and used as our test statistic in the study presented here.

The analysis of the data set clearly suggested that *Septoria tritici* epidemics are driven by a two-step process. The most important step towards disease prediction and fungicide-use optimization is the distinction between years when the crop will be *at risk* from years when it will not. To that extent, the binary approach (epidemic/no epidemic) developed in this study would appear to be particularly useful. The 5% threshold, used to differentiate between high and low years for disease risk, has a practical value for decision making. Using a modelling approach, Paveley *et al.* (2001) tested the sensitivity of optimal fungicide dose to untreated disease on the top three leaf layers during grain filling. From their data, a 5% loss of canopy in a typical crop (max. GAI (Green Area Index) = 6.5) would require much less than 0.4 units of fungicide (where a unit is the label rate) for optimal control. Similarly, based on estimates of yield loss using a model derived from the data of Thomas *et al.* (1989), 5% loss of the upper canopy would not justify treatment above 0.25 dose units in an average crop.

We have found that the initiation of the epidemic can be predicted from temperature in winter (from January until early March) and windspeed at the start of stem elongation (until GS 33 - from late April until early May). In order to efficiently protect the upper canopy of the crop, it is generally acknowledged that, *if needed*, fungicides should first be sprayed at about GS 32 (Anon, 2000). Unlike other models previously developed, the binary model will allow the farmer to have an accurate prediction of the likelihood of a future epidemic by early March in the best case and between GS 31 and 33 at the latest. This, together with the simplicity of the weather variables to measure, makes the model a usable and accurate tool for predicting *Septoria tritici* epidemics and might be extended in a similar way to predict epidemics of other diseases. Also, there now exists a comprehensive network of meteorological stations throughout the UK. As shown for *Septoria tritici* in this work, the predictive models described use widely available weather variables. Therefore, it could be possible to generate maps of areas *at risk* early during the season. These could be published, in the form of an *early warning system*, in the farming press and would meet farmers' need for simple but more accurate "rules of thumb".

ACKNOWLEDGEMENTS

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Oilseed rape and cereal diseases – how are farmers responding to their control?

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ABSTRACT

Evidence from the DEFRA-funded national disease surveys indicated that farmers have reacted differently to disease risk and timing of fungicide sprays for disease control in oilseed rape and cereals. In winter wheat there was a single shift in timing from GS 59 to GS 37 sprays in 1994 and in oilseed rape two shifts, in 1995 and 1999. All these shifts were in response to advice on optimum disease control arising from advice following extensive research. For winter wheat the change came 10 years later, in oilseed rape after only four years. There were only gradual increases in fungicide use in winter barley. The difference in rapidity of response between the two crops is surprising, given that the crops are under common management. We suggest that farmers are responding differently to the scientific evidence and commercial technical information presented to them and indicate why this might be so. The relatively rapid introduction of new chemistry, subtle recommendations on dose and timing and changes in cultivars as they become more disease susceptible complicate decisions and there is a tendency to remain with the familiar. Also of concern is that overall fungicide inputs have not changed despite annual changes in disease risk, indicating that farmers are still applying sprays routinely, rather than in response to the balance between disease pressure and host resistance. This has major implications for effective technology transfer.

INTRODUCTION

Diseases and agronomic practices, including fungicide use, have been quantified in stratified surveys on winter wheat since 1970 (King, 1977), winter barley since 1981 (Polley *et al.*, 1993) and winter oilseed rape since 1986 (Hardwick *et al.*, 1993). Disease control adds significantly to the costs of production, but it can be highly cost-effective when applied efficiently. Many treatments are poorly timed or applied inappropriately and this is in spite of guidance from research. The surveys provide an annual update of data on how farmers' respond to scientific development thorough the monitoring of disease levels and inputs, and indicate how quickly shifts in advice or uptake of new technologies e.g., in the form of new chemistry, are incorporated in their decision making. This paper sets out to examine the data from the cereals and oilseed rape disease databases for pointers to successful uptake of advice and technical developments.

MATERIALS AND METHODS

The methods used in the annual surveys were as described by Hardwick *et al.*, (1989), King (1977), Polley & Thomas (1991) and Polley *et al.* (1993). Farm selection was made on a regional basis. The distribution of crops between regions was proportional to the regional area of winter wheat, winter barley or oilseed rape grown, except for Wales, where additional crops were sampled in order to obtain meaningful figures for the area. The farms for wheat and barley were selected at random from the returns of the previous years June DEFRA Agricultural and Horticultural Census (Anonymous, 1969-2000), those for oilseed rape from farms which provided as representative sample for each county as possible. From 300-400 crops of winter wheat and barley and 95-125 crops of winter oilseed rape were sampled each year in each survey.

The cereal disease surveys were carried out in June and July. Winter barley crops were sampled at the watery-ripe to early-milk growth stages (GS 71-73; Zadoks *et al.*, 1974) and winter wheat sampling was carried out at the early to medium-milk growth stage (GS 73-75). Fungicide treatments designated as being applied at GS 31 (first node) cover the range GS 29-35 (nine of more tillers to five nodes detectable); sprays at GS 39 cover GS 36-48 (six nodes to boot swollen) and those at GS 59 cover GS 49-71 (awns visible to caryopsis watery ripe). Winter oilseed rape crops were sampled on three occasions: late November to early February (mid-leaf production, GS 1.5 to 1.9; Sylvester-Bradley, 1985); late March to early April (one internode detectable, GS 2.0 to green bud, GS 3.3,) and early July (pod ripening, GS 6.3 to 6.5). On each occasion, 25 single plants were assessed from each crop.

For cereals, foliar diseases were recorded as the percentage area of the flag and second leaves affected, using standard area keys (Anonymous, 1976). For oilseed rape, foliar and pod diseases were assessed on a whole plant basis to give a mean percentage leaf or pod area figure for each individual disease (Anonymous, 1979). Stem diseases were assessed as the percentage of stems affected. Details of cultivar, sowing date, previous cropping, pesticide use and method of application were recorded for each surveyed crop. Data were entered into an INFORMIX relational database and analysed to produce tables of figures for interpretation.

RESULTS

Fungicides

Total fungicide use in winter wheat has changed little since 1992, varying between 95 and 99% crops treated (Fig. 1). There has been a gradual increase in the use of sprays applied at GS 39 and a shift in dominance in 1994 from sprays applied at GS 59 to sprays applied at GS 39.

With the exception of 1994, the percentage crops where sprays were applied at GS 31 exceeded all others. Although GS 31 is the main timing for the control of eyespot, since 1998 only less than 18% of crops were treated with a fungicide targeted against the disease at this stage (Fig. 1); years which have seen an increase in the severity of the disease.

Overall fungicide inputs into winter barley have remained fairly stable over the past 10 years with between 90 and 97% crops treated (Fig. 2). Fungicide use at GS 31 has remained fairly static but sprays as GS 39 have shown a steady increase from 50 to 71% over the last 10 years.

Fungicide use in winter oilseed rape has lagged behind that of cereals with 90% crops sprayed being reached in 1998 (Fig. 3), compared with 1985 and 1989 for winter wheat and winter barley, respectively. There has been a major increase in the use of autumn sprays since 1994 and a slight reduction in sprays at flowering. The dominant spray timing in 1992 was at flowering; by 1995 this had changed to the spring and in 1999 to the autumn (Fig. 3).

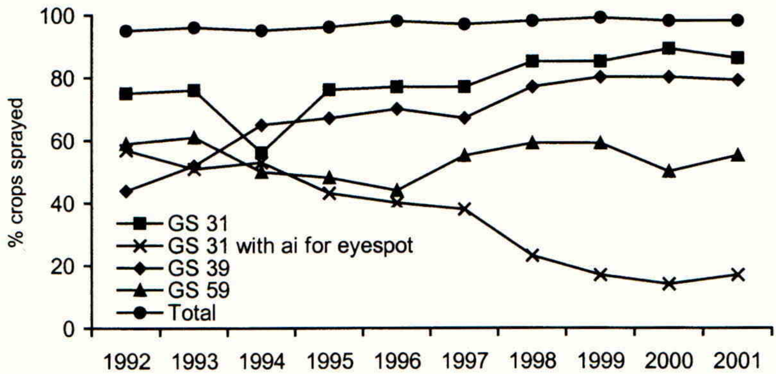

Figure 1 Percentage winter wheat crop treated with fungicide at main growth stages and those applied at GS 31 that contain substances targeted against eyespot (flusilazole, prochloraz, cyprodanil and MBC)

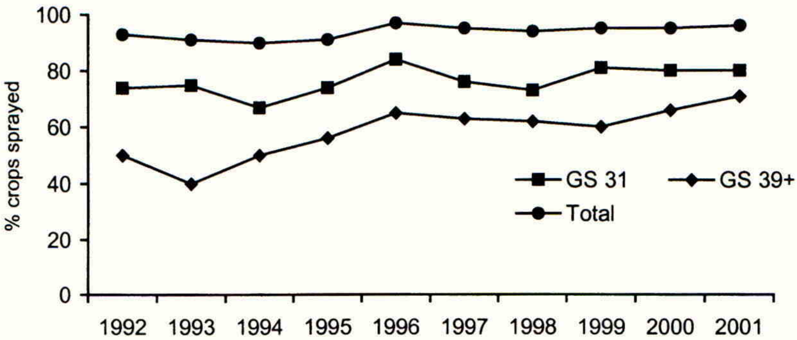

Figure 2 Percentage winter barley crops treated with fungicide at main growth stages

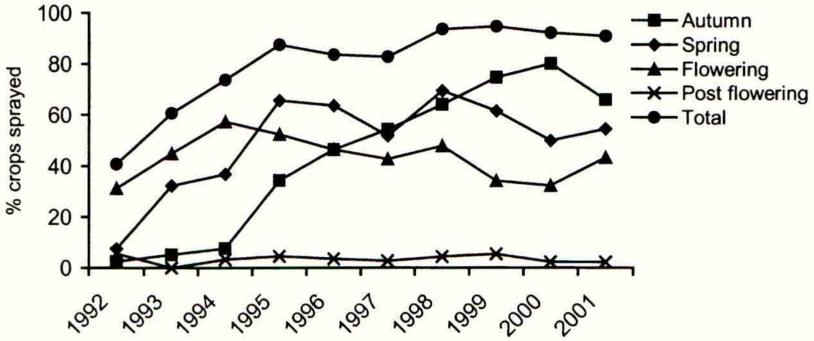

Figure 3 Percentage winter oilseed rape crops treated with fungicide at main growth stages

The introduction of strobilurins fungicides in the mid-1990s resulted in a rapid uptake by farmers reaching over 90% of crops treated within 4 years in winter wheat, with winter barley following a year behind but tailing off at 79% (Fig. 4). The introduction of triazoles for broad-spectrum disease control in oilseed rape showed a more modest uptake, reaching over 90% crops treated after seven years (Fig. 4).

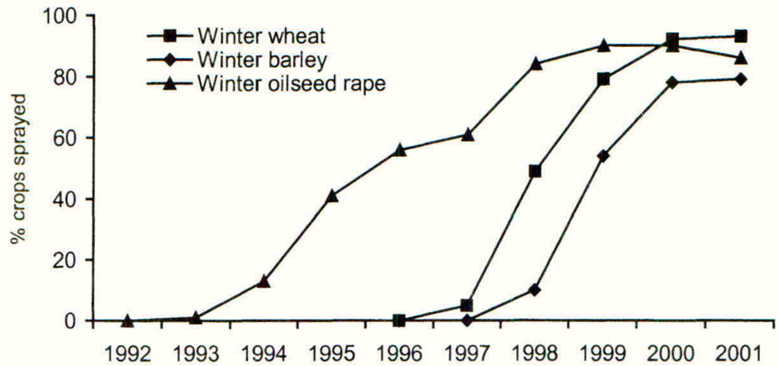

Figure 4 Use of strobilurin fungicides on winter wheat and winter barley and triazoles in winter oilseed rape

Diseases

In winter wheat, sprays applied at GS 39 showed a steady increase, but disease severity fluctuated from year to year (Fig. 5). There was a major contrast between 2000 and 2001, where fungicide input was similar but the severity of septoria leaf blotch is almost 75% lower.

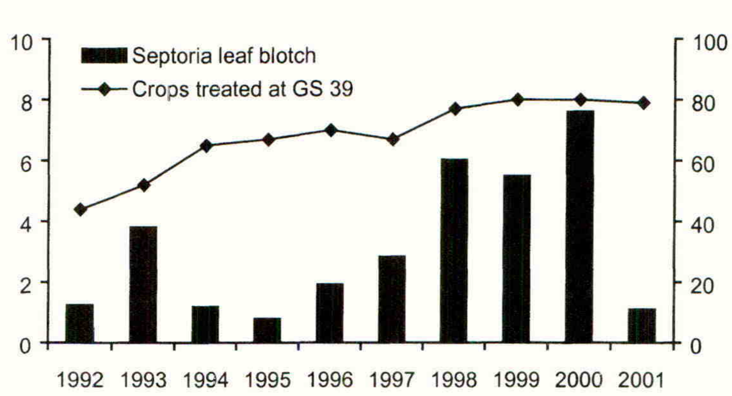

Figure 5 Severity of septoria leaf blotch of winter wheat and fungicide applied at GS 39

As with winter wheat the major disease of winter barley show seasonal fluctuations in severity, but crops treated with fungicides at GS 39 showed a steady increase (Fig 6).

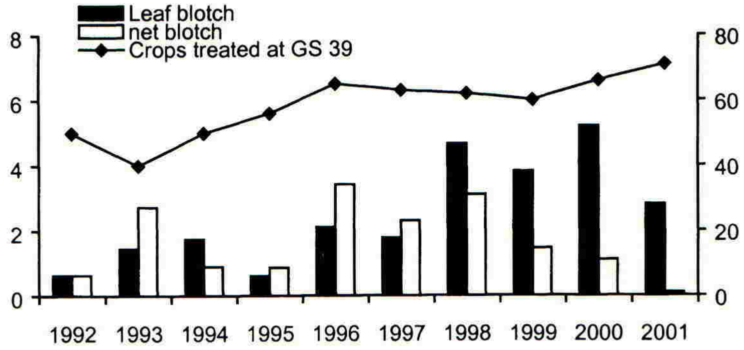

Figure 6 Severity of leaf blotch of winter barley and fungicide applied at GS 37 and beyond

As with cereals, increases in fungicide inputs nationally in oilseed rape did not correlate with a decrease in disease severity (Fig. 7). From 1997, canker severity showed a slight increase as the percentage crops treated in the autumn also rose. Crops treated both in the autumn and spring showed on average less disease than crops treated either in the autumn or spring alone meaned for 1992-2001 (0.55, 0.77 and 1.84 stem area affected by light leaf spot for autumn plus spring, autumn and spring only, respectively).

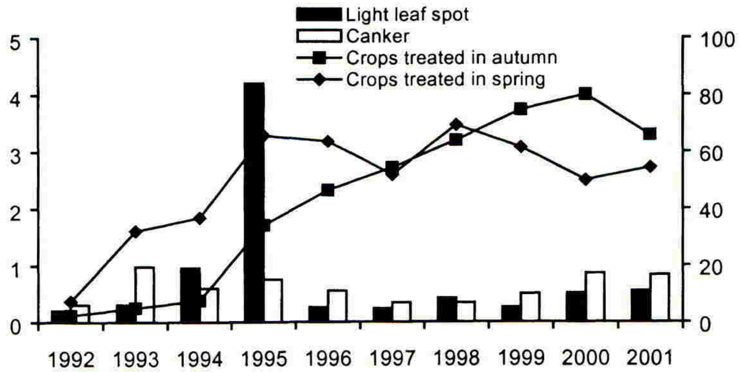

Figure 7 Severity of light leaf spot and phoma leaf spot on winter oilseed rape

Cultivars

In response to a question in the 2001 survey more than 50% of farmers indicated that they did not select cultivars primarily on the basis of their disease resistance ratings. Two popular cultivars of the 1990's were those of Brigadier in winter wheat and Bristol in oilseed rape, each reaching over 20% of the crops surveyed (Fig. 8). The resistance rating of Brigadier to yellow rust fell from 9 in 1995 to 1 in 1998 and that of Bristol to light leaf spot from 5 in 1994 to 2 in 1997.

The number of sprays applied to control diseases in winter wheat were similar, irrespective of the disease resistance rating of the cultivars grown, e.g. the mean number of sprays from 1992-2001 applied to Hereward (a resistant cultivar) was the same as Riband (a susceptible cultivar) at 2.1 sprays per crop. Timings of the applications were also similar.

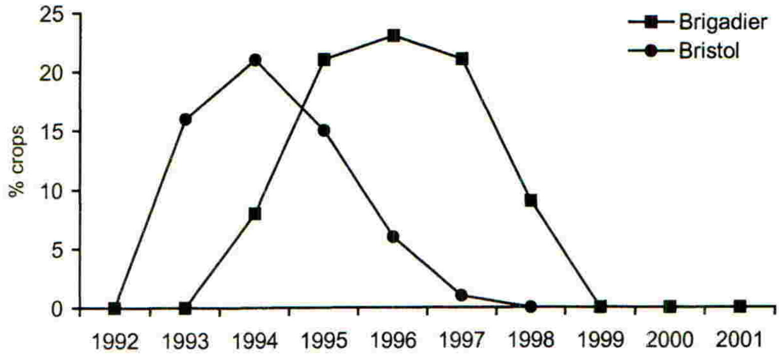

Figure 8 Per cent crops drilled with winter wheat cv Brigadier and oilseed rape cv Bristol

DISCUSSION

Fungicides are applied to crops to control disease in order to increase the net economic output. Fungicide use has remained fairly static over the past 10 seasons while disease levels have fluctuated. Not all treatments were applied at appropriate timings; indeed few oilseed rape growers achieved control of canker with fungicide sprays (Gladders *et al.*, 1998). Other factors have an impact on disease severity. The chief amongst these is the seasonal variation in the weather. It has been argued that all fungicides have achieved is to keep diseases at a level they were before fungicides were introduced so that the agronomic advances in producing higher yielding cultivars more responsive to increased nitrogen inputs can be realised (Hardwick *et al.*, 2000). In some years, where weather conditions are particularly favourable to some diseases, as in the wet season of 2000, fungicide use alone cannot keep diseases under full control.

In response to disease pressure and advice arising from research, there have been changes in fungicide timing. The classic case was the switch in predominance in 1994 from sprays applied at GS 59 to GS 39 in winter wheat. Research in the 1980's indicated that the optimal timing of fungicides to control foliar and ear disease was at GS 39 and not GS 59 (Cook & Jenkins, 1988). However, it was not until 10 years later that the change was made nationally (Hardwick *et al.*, 2001). With winter barley the only change has been a gradual increase in fungicides applied at GS 39. This has coincided with a rise in severity of both leaf blotch and net blotch, for which this timing is appropriate, the assumption being that farmers are responding to disease pressure.

In contrast, over the past 10 years there have been two major shifts in the dominant spray timing in winter oilseed rape; in 1995 from flowering to the spring, with the decline in the incidence of sclerotinia stem rot and alternaria dark leaf and pod spot to the control of light leaf spot (Turner *et al.*, 2000). A further change took place in 1999, from the spring to the autumn for control of light leaf spot and also canker. The trigger in the first case was high levels of light leaf spot recorded in 1995 which developed before spring sprays were applied. Research published in 1995 indicated that for effective control of light leaf spot and canker must begin in the autumn (Gladders *et al.*, 1998; Sansford, 1995; Sutherland *et al.*, 1995), and this has been confirmed in the results from the survey.

The change in response to disease events appears to be more rapid in winter oilseed rape, with two changes in the dominance of sprays within a period of only four years compared with 10 years for winter wheat. Disease increases in cereals have been more gradual, whereas oilseed rape has seen more sudden changes, e.g. the sclerotinia epidemic of 1991 (Turner & Hardwick, 1995). While the majority of farmers do not consider disease to be a prime factor in cultivar selection (Hardwick *et al.*, 2001; Hardwick & Slough, 2001); when major disease events do occur, such as a breakdown of yellow rust in Brigadier, or an instance of high disease pressure on a popular but disease susceptible cultivar, such as Bristol, then farmers do respond quickly by ceasing to grow them.

There are subtle differences in the way in which growers respond to the management of cereals and oilseed rape and it is difficult to understand why this should be so when they are under common management. The rapid uptake of new chemistry in the form of the strobilurins, which quickly demonstrated initial major benefits, contrasts with triazole use on oilseed rape where the difference in performance compared with existing chemistry were not so readily apparent. Oilseed rape is subject to a smaller range of damaging diseases and being, in comparison with cereals, a relative minor crop there is a limited range of fungicide products (less than 30 used in 2001, compared with over 80 used on winter wheat) and sources of information In contrast, cereal farmers are subjected to more commercial pressures with the promotion of numerous products and many (often conflicting) sources of advice.

However, two related issues arise. The first is that farmers do not respond to genetic and agronomic information to adjust fungicide inputs. The second is the emphasis placed on the fungicide responsiveness of cultivars (Paveley *et al.*, 2002). The differences in yield between fungicide treated and untreated cultivars can be indication of their disease susceptibility and growing these cultivars is not helpful in reducing disease risk or fungicide inputs. The disease and fungicide trends indicate that more fungicide does not necessarily mean less disease. Also, a major factor in the equation is the current unpredictability of forecasting high disease risk years and therefore being able to respond appropriately.

The relatively rapid introduction of new chemistry, subtle recommendations on dose and timing and changes in cultivars as they become more disease susceptible complicate decisions and there is a tendency for farmers to continue to use familiar strategies rather than change. Reductions in sources of independent advice also contribute to the slow response to the introduction of best practice. Robust disease forecasts would be of considerable benefit to farmers trying to reduce fungicide inputs and some progress has been made to develop decision support systems. However, further development and validation will be required before users have the confidence to modify current practice.

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International developments in pest risk analysis for phytosanitary decision making: a review of methodologies for pest risk assessment

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ABSTRACT

Pest risk assessment is an essential yet problematic stage in pest risk analysis (PRA) procedure that concerns the extent of the risk and the consequences of pest introduction. In this review the authors discuss current national and international practices of pest risk assessment and the increasingly relevant concerns about invasive species and biosafety. The authors also review research on qualitative and quantitative approaches to risk assessment, taking into account achievements in risk analysis in other disciplines. Consideration is given to the role of subjectivity, the introduction of weighting into risk assessment, issues of uncertainty and expert judgement and the need for a simplified yet rigorous approach to quantitative risk assessment.

INTRODUCTION

The Agreement on the Application of Sanitary and Phytosanitary Measures (SPS Agreement) of the World Trade Organisation (WTO) introduced in 1995 brought about a revolution in plant quarantine. In accordance with the central doctrine of the SPS Agreement, phytosanitary measure that may affect international trade shall be based either on international standards or risk assessment supported by scientific principles and evidence (WTO, 1995). The International Plant Protection Convention (IPPC) is identified in the SPS Agreement as the reference for phytosanitary standards. A series of concept standards has been established under the IPPC, International Standards for Phytosanitary Measures (ISPMs), to assist in harmonising phytosanitary decision-making procedures. However, as there are no specific pest-related international phytosanitary standard equivalent to animal health standard under the International Office of Epizootics (OIE), WTO member governments must base their phytosanitary measures on risk assessment.

The SPS Agreement does not refer to "risk analysis", but uses the term "risk assessment" in a general way. The secretariat of the IPPC uses "risk assessment" to describe a component of risk analysis (Stage 2). Although risk analysis is well known and has a long history in other disciplines, its application for phytosanitary decision-making only emerged in the late 1980s (Griffin, 2002). While the quarantine policies of most countries have historically been based on an assessment of pest or disease risks, pest risk analysis (PRA) has only become prominent as a discrete scientific discipline since the formation of the WTO in 1995 (Stynes, 2002). The term pest risk analysis has been used to refer to the evaluation of the biological factors affecting importation decisions (Khan, 1979). In 1995, pest risk assessment was formally defined as part of PRA and includes factors concerned with trade, economics and environmental impact as well as biology.

Risk assessment is a technique for identifying, characterising, quantifying and evaluating hazards. Irrespective of the application, risk assessment seeks to answer the following questions: a) what can go wrong? b) how likely is it to happen? and c) if it happens, what consequences are expected? (Oryang, 2002). In the wider context of risk analysis, a further question should be resolved: how to manage (eliminate or reduce) the hazard to an acceptable level? A good risk assessment result should be convincing, scientifically based and transparent, and document any areas of uncertainty for further review. In common with risk assessment in some other disciplines, a number of problems must be overcome, e.g. subjectivity, uncertainty, non-quantifiable variables, and the need to integrate information into a simple statement of risk. This paper reviews international developments in methodologies for pest risk assessment.

INTERNATIONAL STANDARDS AND CURRENT PRACTICES

International standards for phytosanitary measures

The International Workshop on the Identification, Assessment, and Management of Risks due to Exotic Agricultural Pests in Virginia, October 1991, endeavoured to harmonise PRA with the proposal for an international standard. A decade later, several international and regional standards for PRA have been established. ISPM2 "Guidelines for pest risk analysis" (IPPC, 1995) was the first, and has been widely recognised and used by national plant protection organisations. ISPM11 "Pest risk analysis for quarantine pest" (IPPC, 2001) is the latest update of ISPM2 and it includes characterisation of pest risk in terms of likelihood of entry, establishment, spread and economic consequences, and documentation of the areas and the degree of uncertainty. Although ISPM11 provides a detailed characterisation of the factors to be considered, it does not recommend any specific methods to conduct a PRA, or how detailed a PRA should be under different circumstances. No guidance is given on how risk should be estimated from each criterion (biological, economic, environmental and social), or how the overall assessment is derived. ISPM11 does explicitly recognise the involvement of uncertainty and expert judgement but offers no specific guidelines concerning them.

Regional and national PRA guidelines

Some Regional Plant Protection Organisations e.g. European and Mediterranean Plant Protection Organisation (EPPO) and North American Plant Protection Organisation have also established PRA guidelines or schemes which followed the general principles of the ISPMs but are more sophisticated and operable. The EPPO pest risk assessment scheme, for example, contains two sections that relate to the first two stages of PRA: initiation, and risk assessment. Section A is a qualitative assessment in the form of a binary decision tree to determine whether a pest has the characteristics of quarantine pest. Section B is a detailed assessment taking the form of a series of questions, to which replies are elicited, expressed on an ordinal scale (a score between 1 and 9). It considers the probability of introduction (entry and establishment) and the economic impact that together express the final assessment (OEPP/EPPO, 1997). This was the first scheme to indicate that some risk factors/questions are more important than others and suggests that risk scores can be weighted, prior to being combined in an appropriate way. This scheme places the *spread potential* of pests within the scope of *economic impact* because the speed and extent of the spread is regarded as more related to the economic loss than introduction. Continued efforts have been made to improve the EPPO scheme but considerable weaknesses remain, e.g. a) how to ascribe a score; b) how to combine the individual scores into a final statement of risk level; c) how to derive weightings and then incorporate these into the risk assessment; d) the existence of duplications and ambiguities in the questions.

Condensed versions of the recognised schemes have also been devised for rapid assessments, e.g. a short, summary qualitative scheme was developed in the UK, which contains the major factors in the ISPM2&11. It can be completed very quickly to decide action against pest interceptions and whether a detailed analysis is required before committing extra resources. The EPPO PRA scheme can then be used for detailed analysis (Baker *et al.*, 1999).

Environmental risk assessment in relation with PRA

Concerns are growing rapidly that guidelines for risk assessment related to invasive species, genetically modified organisms and biosafety are urgently needed. Classic environmental impact assessment used to be human-centred, and although ISPM includes environmental impact, PRA used to consider the impact only within agricultural and forest systems. Guidelines for plant/pest-centred environmental risk assessment outside of agricultural systems are not yet available. An IPPC supplementary standard to ISPM11 was initiated in 2000: Environmental Impact Standard for Quarantine pests, including Invasive Species that are Quarantine Pests (Sequeira, 2002a; Kareiva & Quinlan 2002).

RESEARCH ON PEST RISK ASSESSMENT METHODOLOGIES

Risk assessment methods can be broadly characterised as qualitative or quantitative. Qualitative assessments usually rely on binary or ordinal scoring of risk, whilst quantitative assessments usually employ stochastic and probabilistic approaches. Subjectivity is the weakest point with qualitative assessments, whereas lack of data (experimental or heuristic) limits the application of quantitative approaches.

Characterising risk

Whichever approach is employed, the first step has usually been to characterise the risk factors in some systematic way; this equates to identifying "what can go wrong?". In the EPPO risk assessment scheme, for example, there are about 45 risk factors, each of which takes the form of a question. Identifying and structuring risk factors has not usually involved any particular methodologies but Mindmapping was used by Zhu *et al.* (2000) to facilitate risk identification by disaggregating pest risk into a series of nested risk factors, from general to specific. This highlighted dependencies among risk factors and helped to distinguish factors that are manageable ("control points") as an aid to the selection of risk management measures.

Quantifying specific risk factors

For those risk factors that are amenable to quantification, it is possible to provide detailed predictions. Some computer-based approaches have been used to assess risks associated with specific factors such as establishment potential. Spatial analysis using geographic information systems was employed in the USA to monitor pest outbreaks, to assess the hosts at risk and the risk of spread. It has recently been applied to Medfly, Karnal bunt and citrus canker (Sequeira, 2002b). The automated software, CLIMEX decision-support system developed by Sutherst and Maywald in 1985 was used in Australia and UK to evaluate the risk of establishment of exotic species in relation to climate in a new environment. CLIMEX is applicable to any pest species, provided something is known about its current geographical distribution. The software provides insights into the species' performance in new environments (Sutherst *et al.*, 1991; Baker, 1996; Baker *et al.*, 2000).

Dobesberger (2002) describes some multivariate analysis techniques used to predict establishment potential. Examples include a multiple liner regression model for soybean rust, discriminant analysis for bacterial leaf blight of rice, and logistic regression for pink bollworm.

Probabilistic scenario analysis (PSA) has been used since the 1940s to assess the risks associated with nuclear technology, other engineering applications, financial analyses, and general economic evaluations. A PSA example implemented in PRA was described by Oryang (2002) striving to present PSA as a structured and practical approach. Scenario type risk analyses were also used in Australia in import risk analysis (Stynes, 2002).

Other quantitative techniques may have applications in PRA. Probabilistic risk analysis based on systems analysis and Bayesian probability have long been used in disciplines such as astronautics and nuclear safety. Although there are reservations about the use of Bayesian probability, it is used because there are seldom enough data for a classical statistical analysis (Pate-Cornell & Dillon, 2001). McDowell (2002) describes the tools and skills that are needed to conduct quantitative analysis, discusses various data analysis techniques and predictive models that may be useful for PRA.

Simplifying risk assessment

Pate-Cornell & Dillon (2001) make the point that *"It is generally impossible to include all components and all event scenarios in a PRA* [referring to probabilistic risk analysis], *and an adapted screening procedure is necessary. This screening procedure is meant to filter out the scenarios that are low contributors to the overall risk while retaining the important ones"*. With similar issues in mind, Zhu *et al.* (2002) investigated decision-makings in risk assessment in an attempt to identify the more important risk factors and assess their consistency between different cases. Multivariate statistics (principal components analysis, PCA) and genetic algorithms were employed in an attempt to simplify the risk assessment without losing important information. It was found that: a) risk factors were correlated and therefore redundancy/simplification of risk factors was possible; b) weightings could be derived and risk factors prioritised from PCA provided there were sufficient PRA data; c) high risk is associated with a few particularly influential risk factors; and d) weightings and key criteria differ for different groups of pests. Although considerable simplification was possible, the nature of the simplification depended to a greater or lesser degree on the specific case. Thus, it is unlikely that a general model could be devised.

Uncertainty and expert judgement in PRA

Difficulties in assessing risk under uncertainty are obvious and the use of expert opinion with its associated subjectivity is inevitable. Major uncertainties in PRA concern the behaviour and pest status of non-indigenous organisms in new environments (McDowell, 2002). Inputs based on expert judgement are also essential to developing probabilistic models of pest risk (Dobesberger, 2002). As is often the case, the problem with the precautionary approach is that conservative estimates of the pest risk are used as a way to accommodate uncertainty, with alarming and discouraging results for trade. Bias often exists in subjective judgement. Zhu *et al.*, (2000) suggested using Delphi techniques to reduce the individual biases in expert judgement. Such an approach requires, however, a pool of PRA practitioners to give their opinions independently and adjust the outcome collectively. EPPO, through their PRA panel, uses a similar approach for some PRA cases, although not necessarily by means of a formal Delphi study. Zhu *et al,* (2001) also described various sources of uncertainty and suggested several methods such as using fuzzy logic, sensitive analysis and Monte Carlo simulation to handle these.

CONCLUSIONS AND FUTURE NEEDS

Organisational and interdisciplinary cooperation. Risk assessment has been the subject of much less research in plant quarantine than in a number of other disciplines. It has been left largely to the plant quarantine authorities themselves to devise workable schemes. PRA would benefit from a more academic framework and the involvement of different stakeholders such as research scientists and industry. PRA is an essentially multidisciplinary activity combining environmental science, economics, mathematics and biology. Some aspects have received less attention than others and in particular, guidelines for economic impact assessment need to be developed or reviewed.

Simplifying risk assessment approach. Simplified approaches that maintain the rigor of risk assessment without sacrificing necessary detail and depth is needed to accelerate the phytosanitary decision-making procedure. Such approaches would be particularly attractive to developing country trading partners who may have severe resource limitations. It is inevitable that simplification will lead to loss of accuracy and perhaps a central question concerns where the balance between simplification and accuracy should lie.

Incorporating weighting into PRA. Ideally, weighting should come from historical data of the pests that have already been introduced to new areas. Previous pest introductions and invasions can provide valuable information for PRA but previous data do not necessarily apply to new situations. Some common ground certainly exists in the weightings appropriate for different pest groups and these can provide at least a starting point for new pests.

Improving quantitative analysis. Due to the diversity and large quantity of information involved in PRA, it is extremely difficult to collate it to provide an overall pest risk assessment. Limiting a quantitative assessment to a few risk factors (which is often the case currently) might lead to errors. Methods should be developed for risk ranking and scoring, as well as combining risk scores. Also, it might be asked whether some risk factors cannot be quantified. If so, how are they to be recognised in the final risk assessment?

Finally, a lesson learned from probabilistic study of the space shuttle was that *"conservative estimates should not be mixed with probabilities that represent mean future frequencies of failures. Otherwise the results are meaningless and possibly counterproductive"* (Pate-Cornell & Dillon, 2001). In PRA there may also be a tendency to apply the precautionary principle for those risk factors where more uncertainty exists. When combined with more accurate risk assessments of other factors, the overall result may be equally questionable. Instead the uncertainty should be explicit and open for scrutiny.

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