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Pests and pesticides, risk and risk aversion

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ABSTRACT

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Theoretical and applied literature on risk in decision making for agricultural pest control is reviewed. Risk can affect pesticide decision making either because of risk aversion or because of its influence on expected profit. It is concluded that risk does not necessarily lead to increased pesticide use by individual farmers. Uncertainty about some variables, such as pest density and pest mortality, does lead to higher optimal pesticide use under risk aversion. However, uncertainty about other important variables, such as output price and yield, leads to lower optimal levels of pesticide use. Neglect of these variables in most studies has led to the false assumption that pesticides are always risk-reducing inputs. Furthermore, there is evidence that, in general, the pesticide dosage which maximises expected profit is lower under risk than under certainty. Depending on the balance of forces to increase and decrease pesticide use under risk, in many circumstances the net effect of risk on optimal decision making for pest control may be minimal. The effect on risk of information about pest density and other variables (as in integrated pest management programmes) is discussed. Evidence on this issue is mixed. A range of analytical techniques for analysing risk in pest control is reviewed. Throughout the paper, gaps in the existing literature are identified.

INTRODUCTION

Risk has been perceived and discussed as an area of considerable importance in literature on the economics of pest control in agriculture. Reichelderfer (1980) and Wetzstein (1981) went so far as to claim that risk reduction is the *main* motivation for application of pesticides. While this seems to understate the importance of profit improvements resulting from pesticide use, there is widespread consensus in the literature that, in many

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circumstances, risk considerations influence pesticide use (e.g. Carlson and Main, 1976; Conway, 1977; Reichelderfer and Bottrell, 1985; Antle and Capalbo, 1986; Lichtenberg and Zilberman, 1986a).

The aim of this paper is to review the literature on the impact of risk and risk aversion on decisions to control agricultural pests by application of chemical pesticides. A number of specific issues are addressed including: the impact of risk on control decisions by risk-neutral decision makers, the impact of risk aversion on pest control decisions, the effect of risk on the level of pesticide use, the effect of pesticide use on the level of risk, the impact of information use on risk, which sources of risk may be important in the pesticide problem and whether these sources of risk have been adequately considered in applied studies. In addition a range of methods for examining risk in pest control decisions are reviewed and examples given from the literature. Aspects of the topic which have been neglected in the literature are identified.

A GENERAL RESPONSE MODEL FOR PESTICIDES

The reader may find it helpful in the course of the review to refer to a simple model of yield response to pesticide application. Lichtenberg and Zilberman (1986b) showed that for economic and statistical reasons it is important to represent response to pesticides as a two-stage process: pesticides kill pests, and it is the reduction in pest levels which increases yield. Thus we have pest density (P) as a function of initial pest density (P_0) and a kill function which depends on the rate of chemical applied [$K(C)$ is the proportion of pests killed at chemical dose C]:

$$P = P_0[1 - K(C)] \tag{1}$$

The kill function varies for different pests and pesticides and can depend on timing and environmental conditions. Actual yield (Y) is a function of pest-free yield (Y_0) and $D(P)$, a damage function giving proportional yield loss at pest density P:

$$Y = Y_0[1 - D(P)] \tag{2}$$

$D(P)$ depends on a range of factors and varies for different pests and different crops or pastures. Herbicides may also cause direct damage to the crop yield but for the purposes of this review, the simple two-equation model will suffice:

Profits (π) are given by:

$$\pi = YP_y - CP_c - A - F \tag{3}$$

where P_y is output price, P_c is chemical cost, A is chemical application costs (which are generally independent of dosage) and F is other production costs.

This simple model illustrates the major components of the pest control problem. It can be used as the basis for a range of different types of analysis. For example it could be used to find the threshold pest density above which application of a fixed recommended chemical dosage would produce benefits greater than costs. Alternately marginal analysis could be used to determine the optimal chemical dose. The analysis could be static or, with additional functions, dynamic.

There are a number of parameters in the model which are likely to be stochastic. In equation (1), pest density may be uncertain as a result of uncertainty about the initial pest density, the proportion of pests killed or the chemical dosage actually applied. In equation (2), yield will be uncertain due to uncertainty about pest-free yield, the level of damage and the final pest density. Profits in equation (3) are most likely to be affected by variance in yield and output price. The model illustrates the way these different sources of uncertainty affect the variance of income. For example, uncertainty about the level of pest mortality leads to uncertainty about pest density which in turn affects proportional yield loss, actual yield and, finally, profits. The different sources of uncertainty will be discussed further in the review.

THEORETICAL FRAMEWORKS FOR ANALYSIS OF RISK

Although the first publication on risk in pest management used the concept of "degree of potential surprise" (Hillebrant, 1960), the dominant paradigm for risk analysis in economics has been expected utility maximisation (e.g. Anderson et al., 1977). In response to evidence that many people systematically violate predictions of expected utility theory (e.g. Allais, 1953; MacCrimmon and Larsson, 1979) there has been a recent growth of more 'generalised' versions of the theory (e.g. Machina, 1982; Quiggin, 1982; Chew, 1983). However there have, as yet, been no applications of any of the generalized utility theories to problems of pest control. Of the studies reviewed in this paper, those which account for risk aversion consider the decision maker's objective to be expected utility maximisation or, in a couple of cases, maximin (maximisation of the minimum return). It seems likely that, so long as the probability distribution of net returns is not dramatically skewed, expected utility maximisation will reasonably approximate the more general theories (Quiggin and Fisher, 1989).

Although the studies reviewed here are all concerned with risk, they vary widely in many respects. The assumed objective of decision makers ranges from expected profit maximisation through expected utility maximisation to the extreme degree of risk aversion implied by the maximin principle. Different studies treat different parameters of the pest/pesticide/crop system as being uncertain. There has been a range of analytical frameworks employed including dynamic programming (DP), Bayesian decision theory and stochastic efficiency. The following discussion elaborates on these differences and reviews particular studies.

RISK NEUTRALITY VERSUS RISK AVERSION

The broadest categorization of the risk literature is into those studies which assume risk neutrality and those assuming risk aversion. The assumption of risk neutrality is often made for the purposes of simplicity and tractability (e.g. Marra and Carlson, 1983; Moffitt et al., 1984; Taylor and Burt, 1984; Gold and Sutton, 1986; Johnston and Price, 1986; Zacharias et al., 1986). The first part of this discussion considers the validity of this assumption. Given the extreme statements made by some authors about the importance of risk aversion as the prime motivation for damage control, it may seem that the assumption of risk neutrality is indefensible. However, there have been studies which found that risk aversion had minimal impact on decision making for pest control. Webster (1977) found that for a fungicide-spraying problem in the United Kingdom, the decision of whether or not to spray was *very* insensitive to the degree of risk aversion. Only individuals with extreme decision criteria, such as maximin, would adjust their spraying decision in response to risk. No farmers in a sample of 29 were found to be this risk-averse.

Similarly, Thornton (1984) found that decisions on control of a fungal disease of barley in New Zealand were almost unaffected by risk aversion. In many simulations of disease epidemics, differences in recommendation between expected profit and expected utility maximisation occurred with a frequency of approximately 0.03.

Finally, Pannell (1990a) found that when a range of sources of uncertainty was considered, the variance of income was almost unchanged over a wide range of herbicide dosages. This indicates that the optimal herbicide dosage would not be greatly affected by risk aversion.

In addition to these indications that risk aversion may have little impact on pest control decisions, there is also evidence that many farmers are approximately risk-neutral or only slightly risk-averse (e.g. Bond and Wonder, 1980; Bardsley and Harris, 1987). Finally, Carlson (1984) and Musser et al. (1986) have suggested that risk may not be an important consideration in farmers' decisions on pest control. Taken together, these studies appear to provide some support for use of a risk-neutral framework. However there are reasons to question the general applicability of the results reported by Webster (1977) and Thornton (1984). In Thornton's study, the insensitivity of decisions to risk aversion may have been exaggerated by basing the elicitation of utility functions on a range of payoffs corresponding to just 10 ha. This in itself would not have been a major concern but for the assumption that decisions are independent of the scale of the problem. Given that income variability is positively related to crop area this assumption is unrealistic. In Thornton's study all decisions are made on the basis of a small-scale problem in which risk is bound to be of minor importance. Zacharias and Grube (1984) addressed this issue in their application of stochastic dominance to weed control. They argued that

> "the decision makers will tend to exhibit more risk neutral behaviour when confronted with per acre outcomes rather than farm level returns. If the bounds of the risk preference function are constant across income levels... the rankings [of strategies] associated with per acre and farm level distributions will be different" (Zacharias and Grube, 1984, p.116).

A second factor which may have contributed to the apparent insensitivity of decisions to risk aversion is the use of a simple binary decision rule: don't treat or treat at the recommended dose. This ensures that there are wide ranges of parameter values for which the optimal strategy is unchanged. If dosage rate were treated as a continuous variable, the sensitivity of decisions to changes in all parameters, including risk aversion, would increase. Webster (1977) also used a binary decision rule. The scale of the problem analysed by Webster was not reported in the article.

In addition to these reasons for questioning the conclusions of Webster and Thornton, there are reasons for caution in the interpretation of studies which find a low average level of risk aversion. There is considerable variation in the degree of risk aversion and a substantial number of farmers are highly risk-averse (Bond and Wonder, 1980; Hamal and Anderson, 1982).

Finally, a number of authors have reported finding that risk aversion does substantially affect decision making (e.g. see following discussions of risk aversion and associated modelling techniques). Also, in reports of empirical studies of farmer behaviour, authors have reported finding that reliance on chemical pest control increases as risk aversion increases (Burrows, 1983; Pingali and Carlson, 1985). However the strength of this conclusion should not be overstated. Burrows (1983) conducted an econometric study to determine which variables influence demand for pesticides. In the estimation, the degree of producers' aversion to risk was represented by a very crude proxy variable: the ratio of acres planted in cotton to total acres. Conclusions about risk based on this variable should be very tentative. In another regression study, Pingali and Carlson (1985) found that the level of pesticides used was positively related to the variance of damage. Although they attributed this to risk aversion on the part of decision makers, the evidence is purely circumstantial. They did not recognise that there are several ways in which risk can affect decision making even if the decision maker's objective is to maximise expected profit (see below).

Overall it appears that when analysing pest control decisions, risk neutrality may not be as poor an assumption as one would expect based on some statements in the literature. Several studies based on risk neutrality are reviewed below. However it should be acknowledged that numerous studies have fould that risk aversion does have an impact on pest control decisions. We return to risk aversion after the following discussion of risk neutrality.

Risk neutrality

Of those studies in which risk neutrality has been assumed, the majority have been based on a deterministic decision framework [e.g. most of the studies cited in bibliographies by McCarl (1981) and Osteen et al. (1981)]. This approach can sometimes be defended on the basis that in a strictly linear model, the decision which maximises expected profit in a stochastic framework corresponds to the profit maximising decision in a deterministic framework using expected values of parameters. This implies that if expected profit maximisation is assumed, the inclusion of stochastic parameters in a linear model introduces unnecessary complexity to the analysis without affecting results. Such was the case in studies by Marra and Carlson (1983) and Marra et al. (1989). They explicitly included a discrete probability distribution for the length of the spraying period, but this was unnecessary since all non-linear relationships in the model were approximated by linear functions.

Nevertheless there are several ways in which risk can affect the decisions of individuals whose objective is to maximise expected profit. Tisdell (1986) showed that uncertainty about a parameter value can affect the optimal level of pest control by affecting expected profit. He argued that

> "in many cases the expected level of application is greater under uncertainty than under full information but... this depends on convexity conditions of relevant functions" (p.161).

and that

> "convexity conditions may sometimes be such as to give rise to the opposite consequence" (p.159).

He did not discuss which parameters are likely to increase and which to decrease treatment levels under uncertainty. Auld and Tisdell (1986, 1987, 1988) showed that because of convexity of the relationship between weed density and crop yield, uncertainty about weed density reduces expected yield loss. Auld and Tisdell (1987) argued (but did not prove) that this increases the economic threshold, reducing the overall level of pesticide use. They noted that this does not seem consistent with comments in the literature that risk increases pesticide use. They attributed the difference to the influence of risk aversion dominating the effect of risk on expected profit.

Pannell (1990b) examined a range of uncertain variables in a model of yield response to herbicides under expected profit maximisation. He found that uncertainty about each of the variables considered (initial weed density, weed kill, weed competitiveness, herbicide dosage and weed-free yield) reduced the profit maximising herbicide dosage and increased the threshold density for herbicide treatment. Notwithstanding the quote from Tisdell (1986) above, no cases were found where the expected level of application was greater under uncertainty.

The only study of this type for insect pests was by Plant (1986) who considered uncertainty about pest mortality. Like Pannell (1990b) he found that under expected profit maximisation, uncertainty led to a higher threshold pest density for pesticide use. Although he interpreted this higher threshold as implying a higher level of pesticide use this is incorrect; it actually implies a lower expected level of pesticide use, consistent with Pannell's (1990b) findings.

Another circumstance where risk can affect the decisions of 'risk-neutral' decision makers is where the problem is dynamic (Antle, 1983). Zacharias et al. (1986) tested this hypothesis in their DP study of soybean cyst nematode. They found modest support for the hypothesis, with very small differences between the results of their deterministic and stochastic models.

A third possibility is where the decision maker is subject to a progressive marginal taxation rate. Taylor (1986) showed that the effect of this on decision making is essentially the same as the effect of risk aversion; it makes the decision maker behave in an apparently more risk-averse manner than would otherwise be the case.

Risk aversion

This section of the review examines the widely accepted views that risk increases pesticide usage and that pesticide usage reduces risk. The importance of risk as a determinant of pesticide usage has been emphasised in the literature with the dominant view being that pesticide use reduces risk so that if risk is included in a model, risk aversion will cause the optimal treatment rate to be increased. This is in contrast to other types of inputs, such as fertilizers, which are usually supposed to be used at lower levels under risk aversion than under risk neutrality. Feder (1979) is commonly cited as having established the theoretical basis for the presumed positive relationship between degree of risk and level of pesticide usage. Feder showed that under risk aversion, uncertainty about the level of pest infestation increases the optimal level of pesticide use. However, crop damage was approximated by a linear function, so the effect of uncertainty about pest density on expected profit (see above) was not considered. Auld and Tisdell (1987) showed that, at least for weeds, uncertainty about pest density reduces expected yield loss, and argued that this reduces the probability of treatment being justified. This effect at least partially offsets the positive effect of risk aversion on chemical usage.

Moffitt (1986) in his extension of the M-threshold concept (Moffitt et al., 1984) to allow for risk aversion, further questions the accepted wisdom of greater risk leading to greater pesticide usage. He showed in his theoretical model that, under risk, a higher dosage can be more than offset by less frequent use (i.e. a higher threshold) although this was not found to occur in an empirical application of the approach by Osteen et al. (1988).

A further relevant issue which has received almost no comment in the literature is the fact that the reputation of pesticides as "risk reducing inputs" (Carlson, 1984; Robison and Barry, 1987) appears to be mainly based on analyses which only consider uncertainty about the level of pest infestation or chemical efficacy (e.g. Feder, 1979; Robison and Barry, 1987; Osteen et al., 1988). However, there are numerous other sources of uncertainty in the pest/pesticide/crop system which may or may not result in reduced risk as pesticides are increased. Feder (1979) did consider uncertainty about pesticide effectiveness but was equivocal about its impact on pesticide usage. Chisaka (1977) showed that the level of crop yield loss caused by weeds can be a significant source of uncertainty. Auld and Tisdell (1987) considered uncertainty about crop yield loss in a risk-neutral setting, finding that it would not affect decision making. They did not consider its effect on a risk-averse decision maker. Robison and Barry (1987) commented in passing that the Feder model could be expanded to allow for uncertainty about output price. They observed that

> "two random variables, however, quickly complicate our analysis, forcing us into numerical rather than analytical approaches. Furthermore, we could find the threshold level for N^* as before but the solution would require solving a quadratic formula with few deterministic results" (p.110).

This may explain some of the reticence of most analysts to consider uncertainties other than pest density. However this reticence may have resulted in the perpetuation of a general false impression that pesticides *always* reduce risk. Pannell (1990a) found that for weeds, uncertainty about output price, weed-free yield or chemical damage to the crop leads to greater variance of income at higher herbicide rates. In many environments these may be more important sources of uncertainty than are pest density, pest damage to crops or pesticide effectiveness. In all environments, the question of whether pesticide use results in higher or lower income variability depends on the balance of forces of positive and negative effects on risk. Pesticide usage will result in risk being increased in some circumstances and reduced in others. In an analysis of ryegrass control in wheat in Western Australia, Pannell (1990a) found that the forces balanced so that income variability was almost unchanged over a wide range of herbicide rates.

A number of other authors have considered multiple sources of risk. While they have not provided analytical proof, they have produced some support for the proposition that pesticides do not always reduce risk. Hawkins et al. (1977) conducted budgeting analysis of field results from weed control trials. These would have implicitly included several biological sources of risk including weed density, herbicide effectiveness and weed-free yield. They found that herbicide use increased the standard deviation of returns, which suggests that weed-free yield was the major source of variability in the trials.

In studies by Cochran et al. (1985) and Greene et al. (1985), simulation approaches were used to estimate probability distributions of income for analysis using stochastic dominance techniques. The uncertain variables considered by Greene et al. (1985) were wheat yield, wheat price, soybean price, July temperature and August rainfall. They assumed that these variables followed a multivariate normal distribution which was estimated from 20 years of historical data. Cochran et al. (1985) allowed for uncertainty about the weather, yield, prices, the determination of infestation periods and the calculation of yield loss. It is very interesting that in both these studies, integrated pest management (IPM) strategies, which generally involve reduced pesticide use, were found to be efficient for risk-averse decision makers. In the Greene et al. study, IPM strategies clearly dominated conventional strategies for even the highest level of risk aversion considered. If pesticide use did reduce risk, one might have expected risk-averse decision makers to prefer prophylactic pesticide use. Cochran et al. (1985) used a number of stochastic dominance criteria with different powers of discrimination. IPM strategies were part of the efficient set under all criteria. As the criterion was made more discriminating, strategies involving calendar spraying (i.e. predetermined prophylactic treatments) were removed from the efficient set until the most discriminating criterion resulted in a unique ranking with IPM as the only efficient strategy. Again, if pesticides were risk-reducing, IPM strategies involving lower pesticide use might involve higher risk and not be clearly efficient for risk-averse decision makers.

While these detailed studies are suggestive that pesticides may not reduce risk, there is a need for caution in ascribing this interpretation to the results. It may be that the use of information in IPM strategies is itself risk-reducing. Evidence in support of this is provided by Antle (1988a) who found that pesticides used in an IPM programme were more risk-reducing than those used prophylactically. He also found that the value of information use in IPM strategies was substantially higher for more risk-averse decision makers. Even if lower pesticide use increases risk, information may be sufficiently risk-reducing to more than offset this, making the IPM strategy attractive to risk-averse decision makers. Nevertheless it does appear that the risk-reducing nature of pesticides is by no means proven. This is an issue deserving further attention.

Finally, note that even if pesticide applications do reduce income risk, it does not necessarily follow that a stochastic decision model will lead to greater pesticide usage than will a deterministic model. As discussed earlier, the introduction of risk into the decision process may affect expected profit in such a way that chemical use tends to be reduced. In some circumstances this effect may more than offset increases in chemical usage due to risk aversion.

The remainder of the paper is a review of applied studies which have allowed for risk. The various techniques which have been used are described. Advantages and disadvantages of the techniques are suggested.

BAYESIAN DECISION THEORY

Bayesian decision theory is concerned with the revision of risky decisions in response to information about the problem at hand. Many Bayesian studies calculate the expected value of information to be used in a decision.

Anderson et al. (1977) described the application of Bayesian decision theory to a range of problem types in agriculture. One of the earliest applications of the approach to damage control was by Carlson (1970) who examined the disease control practices of Californian peach growers. He elicited prior probability distributions of disease loss from growers and used these to show that if the number of applications of chemicals is optimally adjusted in response to disease forecasts, chemical usage can be substantially reduced.

Webster (1977) conducted a Bayesian analysis of a fungal parasite problem on wheat. He elicited (quadratic) utility functions from farmers and, as discussed earlier, found that the decision of whether to spray was very insensitive to risk attitudes. In a follow-up study, Menz and Webster (1981) used a Bayesian approach to estimate the expected value of information which would be provided by a hypothetical advisory scheme proposed by Webster (1977). They found that the expected value of information was very high so that benefits of the proposed scheme would be very likely to outweigh costs. In a later publication, Webster (1982) gave a general discussion of the value of information in pest control and presented examples for a disease control program. The analysis was simplified by assuming expected profit maximisation and by assuming that the values of different types of information are additive and independent.

Mumford (1981) emphasised the subjective aspects of pest control decisions. He found that pest control decisions by members of a particular group of surveyed farmers was consistent with a simple Bayesian model in their pest control behaviour. He assumed that the objective of the more risk-averse farmers in the group approximated to 'maximin', although Webster (1977) found no farmers in a group of 29 who were that risk-averse.

Thornton and Dent (1984a, b) focused on revision of optimal disease control strategies in response to information on climate and disease information levels. They described their approach as "implicitly Bayesian" (Thornton and Dent, 1984a, p.123) and presented a framework for implementing it for use by farmers. They found that the expected value of climate and disease level information "increases with decreasing partial risk aversion, since the value is dependent on the recommendation not to spray, risk-averse individuals being loath not to apply spray" (Thornton and Dent, 1984b, p.241).

The study by Antle (1988a, b) might also be considered as "implicitly Bayesian" in its emphasis on risk and sequential decision making. Interestingly, in a case study of IPM strategies for tomato production, he obtained the opposite result to Thornton and Dent (1984b); greater degrees of risk aversion were associated with substantially higher values of information. Another interesting finding was that although insecticides as a group were found to be marginally risk-reducing inputs, those pesticides applied with relatively low frequency in the IPM programme were found to be substantially more risk-reducing than those applied prophylactically. Clearly the degree of risk reduction obtained from pesticide use depends not just on the level of pesticide used, but also on the way it is used. Antle's finding suggests that information which aids in determining optimal pesticide use may be more risk reducing than pesticides per se.

Moffitt et al. (1986) examined the value of publicly provided information on pest levels in a situation where private scouting services were available. They found that the value depended on the reliability of public information. If it were slightly less reliable than private information, public information still had a positive net value to farmers by virtue of its lower cost. However, below a certain level of reliability, public information had no value.

Stefanou et al. (1986) presented a Bayesian model incorporating decisions on both whether to scout and whether to spray. They applied the model to cotton lygus bug in California and conducted wide-ranging sensitivity analysis.

The studies discussed above all allowed for risk aversion on the part of decision makers. Bayesian decision theory can also be applied in a risk-neutral setting. For example Johnston and Price (1986) assumed risk neutrality in calculating the expected values of perfect and imperfect information in the problem of stored grain insect control. Cammell and Way (1977) applied a risk-neutral Bayesian model to estimate the value of forecasting black bean aphid populations. They found that basing treatment decisions on this information was substantially more profitable than routine treatment or no treatment.

All of the farm level studies cited in this section treat the pesticide as a binary variable to be applied at the recommended rate or not at all. There does not seem to have been an application of Bayesian decision theory in which treatment dosage has been treated as a continuous variable. It is also notable that none of these studies examine a problem of weed control. It appears that a Bayesian approach to probability revision is highly applicable to problems of tactical weed control.

STOCHASTIC EFFICIENCY

In the Bayesian studies described above, particular utility functions were elicited or assumed for use in the analysis. If a specific utility function is used then it is possible to give an unambiguous ranking of all strategies under consideration. However, these rankings are not necessarily consistent with the preferences of individuals who do not have the exact utility function used in the analysis.

Stochastic efficiency analysis is used to generate information which is applicable to broadly defined groups of decision makers. There are a number of different stochastic efficiency criteria used depending on how broadly defined a group of decision makers is being targeted:

(a) first-degree stochastic dominance (FSD) applies to all decision makers who prefer more income to less (Quirk and Saposnik, 1962);
(b) second-degree stochastic dominance (SSD) applies to those decision makers from (a) who are risk-averse (Hadar and Russell, 1969);
(c) third degree stochastic dominance (TSD) applies to those decision makers from (b) whose degree of risk aversion decreases with increasing wealth (Whitmore, 1970);
(d) stochastic dominance with respect to a function (SDWRF) is applicable to decision makers whose degree of risk aversion lies between that of two given utility functions. The breadth of the decision group can be varied by adjusting the functions which define the bounds (Meyer, 1977a, b).

The greater generality of these techniques is only obtained at the cost of reduced specificity of their recommendations. In general they do not provide a unique ranking of the available strategies. Rather they identify groups of strategies which are 'efficient'. All elements of the efficient set of strategies would be preferred to all strategies not in the efficient set by *all* members of the relevant group of decision makers. A potential problem with the technique is that the efficient set can be vary large, in some cases including most of the available strategy options. In this circumstance the information provided by the technique is of little value. Greater discriminatory power can be obtained by more closely defining the group of decision makers (e.g. using third degree, rather than second degree, stochastic dominance) and/or by using techniques such as convex set stochastic dominance (Cochran et al., 1985). However, as Tolley and Pope (1988) observed, "second degree stochastic dominance has been easily implementable and continues to have a preeminent place in efficiency analysis" (p.694). Tolley and Pope noted that sampling errors in the estimation of probability distribution functions are usually not considered. They showed that if sampling errors *are* considered, the size of the efficient set is increased even further.

Finally in this background information on stochastic efficiency, it should be noted that a very common method of identifying efficient strategies for risk-averse decision makers is E-V analysis (Markowitz, 1952). However E-V analysis has been widely criticised because it has very strong requirements for validity (Lambert and McCarl, 1985). Either returns must be distributed normally or the decision maker must have a quadratic utility function. The former is frequently not the case and the latter is generally dismissed as unrealistic because it implies increasing risk aversion with increasing wealth.

The literature on the economics of pest control includes five applications of stochastic dominance: two in problems of insect control, one on a disease problem, one on weeds and one encompassing weed, pest and disease control. Between them, these studies have included most of the efficiency criteria described above (all except TSD).

Papers by Greene et al. (1985) and Cochran et al. (1985) were described above in the discussion of whether pesticides are risk-reducing inputs. Greene et al. (1985) used SDWRF to rank various strategies for insect pest control in soybeans. They found that IPM strategies are efficient relative to prophylactic spraying for a wide range of risk attitudes. Cochran et al. (1985) used FSD, SSD, SDWRF and SDWRF with convex set stochastic dominance to evaluate strategies for Apple scab control. Again IPM strategies were favoured.

Moffitt et al. (1983) used FSD and SSD to evaluate a range of alternative citrus thrip control methods for inland Southern California orange groves. Of the eight strategies considered, six were in the FSD efficient set while three were in the SSD efficient set.

Zacharias and Grube (1984) examined a range of crop rotations in conjunction with different weed control methods. They used SDWRF to examine strategy rankings for risk-averse, risk-neutral and risk-preferring decision makers. Their conclusions about the effect on risk of using information to adjust herbicide usage were the reverse of Antle's (1988a):

> Successively altering herbicides on an annual basis as compared to applying a single major herbicide was found to increase both net returns and risk" (p.113).

Finally Musser et al. (1981) compared the results of E-V analysis and FSD/SSD in ranking four sets of strategies for controlling weeds, pests and diseases in Georgia. They found that, in an E-V framework, both conventional strategies and IPM strategies were efficient. IPM had higher mean net income but also higher variance of income and so was not clearly preferred to conventional control in an E-V framework. However IPM was found to be FSD over conventional strategies and so would be preferred by all decision makers regardless of their risk preferences. Note again that use of an IPM strategy was not found to reduce risk. Apparently in both of these studies, chemical sprays *were* risk-reducing and information was not sufficiently risk reducing to offset the increase in risk resulting from lower chemical use.

Studies employing an E-V approach to assessing risk in pest control have included Carlson (1970), King et al. (1986) and Lybecker et al. (1988).

DYNAMIC PROGRAMMING

Pest control in a crop or pasture may have either positive or negative carry-over effects in subsequent crops or pastures. For example, one of the advantages of including the legume crop, lupins, in rotation with cereals in Western Australia is that they allow use of the herbicide simazine for weed control, reducing the costs of grass weed competition and control in subsequent cereal crops. In general, the number of weed seeds with potential to germinate in a given year depends on the degree of control in previous years. A negative effect of weed control in crops is that the density of subsequent pastures can be reduced. Dynamic factors such as these may affect optimal weed control practices.

A dynamic analytical framework is even more important for problems of pest and disease control. Reproduction rates are very high for these organisms so that infestation levels can increase rapidly. For most weeds, the life cycle takes at least a year so that population dynamics are not as essential to the economic problem as they are for pests and diseases. Techniques used to address dynamic problems include simulation (discussed in the next section) and DP.

Christine Shoemaker stands out as the major contributor to the literature in the DP field, particularly for management of alfalfa weevil. In two of her papers, stochastic DP was used to assess the effect of risk on decision making (Shoemaker and Onstad, 1983; Shoemaker, 1984). In Shoemaker

(1984) the issues of multiple pesticide applications and carryover of pesticide from one season to the next were considered. As well as using more than one variable to determine whether to treat, she has also considered more than one type of treatment: pesticide application and biological control (Shoemaker and Onstad, 1983).

Taylor and Burt (1984) used stochastic DP to determine whether or not to spray and/or fallow to control wild oats in spring wheat in the U.S.A. Pandey (1989) used deterministic and stochastic DP to determine optimal herbicide rates for control of wild oats in Western Australia.

There has also been an application of stochastic DP to a problem of disease control. Zacharias et al. (1986) used stochastic DP to evaluate management strategies for controlling soybean cyst nematode. They tested and upheld Antle's (1983) hypothesis that risk-neutral (i.e. expected profit-maximising) decision makers can respond to risk if the problem is dynamic.

In each of these studies, expected profit maximisation was assumed to be the objective; there was no allowance for risk aversion on the part of decision makers.

The obvious advantage of DP as a solution method is its efficient handling of dynamics. The main disadvantage is the 'curse of dimensionality': as the number of state variables in the model increases, the number of calculations required for solution increases exponentially and can become impractically large. Hence DP generally requires that complex systems be greatly simplified before they can be analysed.

Another facet of DP which may be considered a disadvantage is that it can only handle discrete decision problems. Only discrete alternative strategies can be evaluated, not continuous variables such as chemical dosage, although this can be overcome to a degree by considering a discrete number of chemical dosages as alternative strategies (e.g. Pandey, 1989).

SIMULATION

Simulation models of various kinds have been used in a number of different ways to evaluate the economics of pest, disease or weed control. Risk aversion has been analysed in a number of ways in these studies: by numerical solution of the expected utility maximisation problem (Lazarus and Swanson, 1983; Thornton and Dent 1984a, b), by E-V analysis (King et al., 1986) and by stochastic dominance approaches (Cochran et al., 1985; Greene et al., 1985).

An advantage of simulation models is that they allow estimation of technical relationships which would be expensive, time-consuming or impractical to estimate from field experiments. A second advantage is that, relative to optimization techniques such as DP or mathematical programming, they allow more detailed representation of biological and technical components of the system (Shoemaker, 1984). A disadvantage is that in most economic applications they must be solved numerous times to reach a conclusion. For example, Shoemaker (1979) noted that to conduct a similar analysis to that carried out by a particular DP model, a simulation model would have to be solved 1 380 000 times. Simulation models do not imply use of a particular economic framework; rather they can be used to provide inputs to economic analyses of several types.

There have been several studies in which simulation models were used to estimate probability distributions of technical parameters which were then used to estimate thresholds under risk. For example Thornton and Dent (1984a; b) described the design, operation and implementation of such a system for evaluating control of the fungal disease *Puccinia hordei* in New Zealand barley crops. The effect of climatic variation on the variance of profit was estimated by simulation and used to calculate thresholds under risk aversion. Their study was discussed earlier in the context of Bayesian decision theory. King et al. (1986) estimated thresholds for weed control in continuous corn (*Zea mays*). Although they did not consider the impact of risk aversion on the decision, they estimated the variance of profit for different strategies. Lazarus and Swanson (1983) did allow for risk aversion in their evaluation of rootworm control in corn. Although their representation of biological relationships was relatively simplistic, this allowed them to analyse a more complex decision problem. They estimated not just pest thresholds at which chemical application was justified, but also a higher threshold at which it was worth rotating to another crop.

A somewhat similar use of simulation models has been to estimate probability distributions of net returns for evaluation using stochastic dominance techniques. Cochran et al. (1985) used this approach in their application of convex set stochastic dominance to evaluation of various apple scab control strategies, as did Greene et al. (1985) in their use of generalised stochastic dominance to evaluate soybean integrated pest management strategies.

ANALYTICAL/NUMERICAL APPROACHES

In a number of applied studies of risk in pest control, direct numerical solution of theoretical models has been employed. Moffitt et al. (1984) numerically solved for the optimal parameters of their M-threshold model for corn nematode control under uncertainty about pest density. Osteen et al. (1988) conducted a similar study of corn nematode control which, unlike Moffitt et al. (1984), allowed for risk averse decision making. Liapis and Moffitt (1983) used the exponential utility moment generating function approach to calculate certainty equivalents of alternative cotton pest control strategies under different degrees of risk aversion. The use of this approach was attacked by Scott et al. (1986) but defended by Liapis and Moffitt (1986). Lazarus and Swanson (1983) used numerical solution in conjunction with a simulation model to calculate pest density thresholds for application of pesticide and for switching crop rotation.

The numerical solution techniques employed in these studies can be very useful when the problem is not amenable to analytical solution or to solution by common optimization techniques such as DP or LP. This can be the case, for example, when the profit function has more than one local optimum, when it has several state variables or when close links with a simulation model are desired.

In a number of studies relevant to pesticide application, Lichtenberg and Zilberman have used marginal analysis to derive optimal regulatory standards for reducing the probability of negative effects on health (Lichtenberg and Zilberman 1988a, 1988b; Lichtenberg et al. 1988). In each of these analyses allowance was made for "aversion to uncertainty." No other studies of public or social pest control problems have considered risk except by conducting sensitivity analysis (e.g. Pannell, 1984; Denne, 1988).

RELEVANCE FOR DEVELOPED AND DEVELOPING COUNTRIES

Almost all studies cited in this review deal with problems in developed countries. However the review also has relevance for developing countries; the biological and economic relationships are similar although some parameters differ. Particularly important for this topic is the higher level of *absolute* risk aversion found amongst farmers in developing countries (Binswanger, 1980; Hamal and Anderson, 1982; Antle, 1987) compared to their counterparts in developed countries (Bond and Wonder, 1980; Bardsley and Harris, 1987; Myers, 1989). (These studies find similar ranges for *partial* risk aversion in developed and developing countries, and since incomes are lower in developing countries this implies that they have higher *absolute* risk aversion). Given the conventional wisdom about pest control reducing risk we would expect farmers in developing countries to adopt pesticides with enthusiasm. However if the conclusion in this review is correct and pesticides do not always reduce risk we should not be surprised if adoption of pesticides is no greater than for other inputs such as chemical fertilizers.

Secondly, if information about pest density increases in value with increasing risk aversion (as found by Antle 1988a, b), we would expect pesticides to be more acceptable to farmers in developing countries if they are promoted as part of an IPM package involving scouting for pests before making spray decisions. However, further work is needed in this area as

Thornton and Dent (1984a, b) found decreasing information value with increasing risk aversion.

CONCLUSION

In the course of this review, some commonly made assertions about the influence of risk in pest control have been challenged. In addition some gaps, unresolved issues and possible methodological deficiencies in the existing literature have been identified.

There are a number of sources of uncertainty which affect decision making for pest control. It was concluded that for some of these sources of uncertainty (e.g. pest density, yield loss per pest, pesticide effectiveness) pesticide application acts to reduce risk. However, for others (e.g. pesticide damage to crops, pest-free crop yield, output price) pesticide application can increase risk. Thus the validity of the usual assumption that pesticides reduce risk depends on the relative importance of these different sources of uncertainty. Thus it is important to consider more sources of risk than the ones most commonly considered: uncertainty about pest density and pest mortality.

It was noted that, due to nonlinearities in the biological relationships, risk can affect pesticide decisions even if the farmer's objective is to maximise expected profit. Evidence in the literature indicates that the optimal level of pesticide use for risk-neutral decision makers is lower under uncertainty. This issue has received attention with regard to weeds but has been relatively neglected for insects and diseases. On the other hand, applied studies of the impact of risk aversion on pesticide decisions have been conducted for insects and diseases (albeit for a limited range of sources of uncertainty) but not for weeds.

Information about the crop/pest/pesticide system not only increases expected profits but can also be a very useful source of risk reduction in its own right. On the other hand some studies have indicated that use of information results in higher levels of risk. The impact on risk of information use needs further investigation to resolve this conflicting evidence. So far, studies of information use in pest control have focused on information about pest density. Attention should also be given to information related to other variables such as pesticide efficacy and pest-free yield.

The review has covered a wide range of analytical techniques, with different strengths and weaknesses, which can be used to analyse risk in decisions on control of pests. Regardless of the technique used, virtually all published applied studies have treated the pesticide as a binary variable to be used at recommended rates or not at all. There appears to be scope for analysing risk and risk aversion when input level is treated as a continuous variable. With increasing concern about externalities from high pesticide use (e.g. through spray drift, chemical residues in food, resistance development) the economics of reducing chemical rates, including its impact on risk, is a topic ripe for analysis by agricultural economists (Pannell, 1988a, b, 1989).

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