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Towards some principles of good practice for decision analysis in agriculture[*]

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Because the analysis of risky choice in agriculture and rural resource management is important but difficult, we argue that there is a need for some agreed principles on how to proceed. This paper is intended as a first step to this end. We start with the proposition that the importance of risk aversion has generally been exaggerated relative to the task of finding better ways to deduce relevant and reliable probabilities. Getting better probabilities demands careful thought, drawing on what is know about the pitfalls and on evolving insights into better ways of proceeding. Our aim is to stimulate a debate leading to a clearer consensus about better practice in these matters.

Key words: Decision analysis, risk, uncertainty, probabilities, subjectivity, rational choice

1. Introduction

Agricultural production is a risky business, and risk analysis and risk management tools have become increasingly popular in recent years. Unfortunately, some analysts have been rather cavalier in their use of the theory and methods of decision analysis. Given the complexity of risk analysis, it is hardly surprising that some mistakes have been made and that there is scope for disagreement on how to proceed. With mainly an econometric focus, Just (2000, 2003) and Just and Pope (2001) have assessed possibilities and sound principles for research on agricultural risk.

In this paper we seek to do the same for prescriptive decision analysis. The aim is to identify some of the main areas of difficulty and possible confusion in risk analysis in agriculture and to suggest some steps towards better practice. Our proposed principles of good practice are based on reasoned argument or relevant findings in the literature. In reality, not all analysis can or should strictly follow any formal rules; what is best will, of course, vary from case to case. However, we think it is useful to try to develop some guiding principles that will find broad acceptance and application.

Some of our suggested principles may be contentious, in which case we hope that this paper will stimulate a discussion leading to a clearer consensus about how important risky choices in agriculture can best be tackled.

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This paper is divided into six main sections. After this introduction there is a section on modelling principles, where we discuss the need for systematic analysis of risky choices in agriculture. In the third section we turn to expected utility and risk aversion, where the importance of these aspects in normative decision analysis is discussed. Then there is a small section on the state-contingent approach, where we speculate about the future use of this new theory in prescriptive decision analysis. Fifth, we discuss probabilities for risk assessment. Here we address better ways to obtain the probability distributions that describe the risk that farmers or farm policy makers face. The main emphasis in the paper is on this topic since we consider it to be the most important and the weakest aspect of current practice in applied risk analysis in agriculture. It is also likely to be the most contentious since we base our treatment on a subjectivist view of probability, in contrast to the relative frequentist view on which most agricultural and resource economists were reared. The paper ends with some brief concluding comments.

2. General principles of modelling

2.1 The importance of accounting for risk

Farmers have always tried to find ways to manage risk by achieving better control over the production processes and by various forms of risk sharing. In addition, for many decades governments around the world have intervened to try to help farmers cope more effectively with risk. Yet in agriculture, as in other areas of human endeavour, risk remains an inevitable feature of life. But does risk in farm and policy decision making really matter? Clearly, some risks, such as the possibility of an outbreak of a highly contagious animal disease or an environmental catastrophe, must be taken seriously (e.g., Kunreuther 2002). Other risks, such as a temporary feed shortage on a grazing farm or low returns from a particular cash crop, can usually be ‘ridden out’ by a reasonably solvent and competent farm operator. Evidently, only ‘important’ risks are worthy of systematic analysis – a point not always reflected in the professional literature.[1] Our starting point, therefore, is that there are important risky choices faced by policy makers and farmers that warrant systematic analysis to assess the ‘best-bet’ course of action.

Risk can be important because, in a nonlinear system, even setting input variables at their mean values will give a biased (and usually over-estimated) value of the payoff measure (Anderson 1976; Hardaker *et al*. 2004a). This effect, which Hardaker *et al*. (2004a, pp. 8-11) call downside risk, occurs whether decision maker is risk averse or not. Risk analysis is needed to deal with it.

In addition, if a decision maker is risk averse, an analysis of risky choice based on maximising expected money value will generally not lead to the option that will be most preferred (Arrow 1951; Robison and Barry 1987). The size of the bias depends on the riskiness of the particular decision and on the degree of risk aversion of the decision maker.

These considerations lead us to our first proposed principle:

Principle 1. All decisions are risky, some more than others. A decision analysis that ignores risk may be flawed, perhaps seriously so.

This principle partly based on the proposition that, because systematic risk analysis requires more information and judgments about the uncertainties to be faced than

[1] The problems reported in the literature seem too often to have been chosen because abundant data were available rather than for their importance. That is rather like the drunk who is looking for lost car keys, not where they were lost in the dark, but under a street light, on the mistaken basis that this is where he can see.

deterministic analysis, it should lead to an estimate of expected consequences that is at least no worse than that obtained by deterministic analysis (Morgan and Henrion 1990). Moreover, by having information about the distribution of the consequences, a better assessment of the risks can be made, leading to what should be a better choice.

Advocates of deterministic analyses often claim that 'risk' is accommodated by sensitivity analysis. Yet, at least as conventionally applied, sensitivity analysis is a poor substitute for a proper risk analysis. As Reutlinger (1970) argued, the results of varying selected uncertain coefficients are of little use unless accompanied by a thoughtful specification of their probability distributions, or at least of their feasible ranges. Moreover, the usual one-by-one variation of uncertain coefficients gives no attention to possibly crucial stochastic dependencies between variables.

Anderson (1976) argued that 'full disclosure of information and its quality' is important in modelling. In analyses under assumed certainty, disclosing uncertainty about key coefficients is rare and may even be viewed by some as an admission of weakness. On the other hand, risk analysis requires careful consideration of these uncertainties and, at least for major sources of uncertainty, the explicit modelling of the uncertainty as part of the analysis. Provided the data, assumptions and results are presented in an informative way, risk analysis therefore provides more transparent decision support.

Many people baulk at the inevitable subjectivity of most risk analyses. Certainly, there is ample evidence of the fallibility of human judgment. The difference is that risk analysis exposes the subjectivity while analysis under assumed certainty typically hides it. Systematic risk analysis does not overcome the fallibility of human judgments, but the need for analysts to think more deeply about the uncertainty associated with the problem at least means that the bias inherent in single-valued estimates may be reduced (Morgan and Henrion 1990).

Finally, on the demand side, many questionnaire surveys have shown that farmers view some risks as worrisome (e.g., Wilson *et al*. 1993; Martin 1996; Meuwissen *et al*. 2001; Koesling *et al*. 2004), suggesting a need for farm management consultants and advisers to make use of modern decision analysis tools to support farmers in coping with these important risks. Some recent spectacular failures in public policies relating to risk management, in agriculture but more so in other areas, imply a need for better risk analysis in public decision making.

2.2 The difficulty of risk analysis

Despite the arguments advanced above, tackling the evaluation of risky choices can be difficult and demanding. The difficulty at farm level arises in part because agricultural businesses, as other businesses, are often best modelled in a system context. That implies a need to cast the decision analysis in a context of the whole-farm (or the whole-firm and household), rather than in a partial context. A system view includes dynamic, stochastic, biological, technical, financial and human factors that interact (Pannell *et al*. 2000). Further, within a broad system context, all possible on-farm and off-farm alternatives and all the risks bearing on those activities should ideally be considered in the model of agricultural decision analysis (e.g., Anderson 1982; Richardson and Nixon 1986; Hardaker *et al*. 2004a).

Even in a marginal analysis, there is usually more than one uncertain quantity to be considered, and in a whole-farm analysis there will be many. Consequently, as discussed below, stochastic dependency between variables may be an important, raising difficult and often neglected issues (e.g., Reutlinger 1970; Taylor 1990; Smith *et al*. 1992; Livny *et al*. 1993; Hardaker *et al*. 2004a).

Evidently, fully comprehensive modelling is likely to be difficult, sometimes perhaps impossible. Even if technically feasible, too much complexity makes a model difficult to build, debug and use, and may give results very little better than could have been obtained from a simpler representation. Morgan and Henrion (1990, ch. 12) argue that a complex model often will do a worse job than a simpler one. They mention the difficulties that have occurred when attempts were made to construct and use the large social, economic, and environmental global models in the 1960s and 1970s. It is therefore best to keep the model as simple as is judged reasonable. The intention with decision analysis is not to give exact answers, but to highlight relative consequences of different alternatives, and to develop insight and understanding. Hence, as always, judgment is needed in the decision modelling task (Burmaster and Anderson 1994). A risk analysis need only be as sophisticated as is necessary to provide the decision maker with a good answer to the relevant problem in a timely manner (Richardson 2004; Hardaker *et al*. 2004a). These choices are essentially 'artistic' in the same way as a portrait painter seeks to capture those features of a face or personality that seem most important for the task in hand. Hence, our second principle:

Principle 2. Risk analysis is 'the art of the possible'**.**

By this we do not mean that the difficulty of the task should deter an analyst from attempting some modelling. Only exceptional people have the capacity to make wise decisions intuitively. For most of us, some decision analysis is likely to be better than none, at least for important risky choices (Arrow 1951).

By the nature of the artistry entailed, there can be few firm guidelines on how to do decision analysis well. However, drawing on Clemen (1996, chs 2 and 3), we can list some basic steps:

1. identify and structure the values and objectives;
2. structure the decisions (often sequential) into a logical framework;
3. identify the risky events and dovetail them with the sequence of decisions;
4. identify and evaluate the consequences of the various decision and event sequences in terms of the relevant objectives;
5. refine and clarify the definition and specification of all elements of the decision model;
6. analyse and solve the decision problem to be able offer guidance to the decision maker.

The preliminary structuring steps 1 to 3 above are very important since it is through these steps the analyst is forced to understand the problem and all its different aspects. It is also in the structuring process that 'artistic' choices have to be made about what to do and how to do it. For example, it is important to think carefully about which uncertainties should and not should be represented by probability distributions (Morgan and Henrion 1990, pp. 50-56). Vose (2000, pp. 6-12) suggests that a preliminary informal analysis can be used to exclude from the model those uncertainties that have a low impact on the riskiness of the consequences.

Tools that are useful in the early stages of problem specification include influence diagrams and outline or more complete decision trees (e.g., Clemen 1996; Hardaker *et al*. 2004a). Once the structuring stages are completed, there is a wider range of methods that can be used for decision analysis. This is not the place to describe the latter methods as there are several texts that do that.[2] What is important to note is the great increase in capacity for risky decision analysis that has been brought about by the increased availability of powerful, special-purpose software. Tasks that 30 years ago or more took many days of work can now be completed almost with the click of a mouse. The very ease of use of some of these methods

[2] Our own overview of what is useful is, of course, to be seen in Hardaker *et al*. 2004a.

brings its own dangers, notably the risk that analysts may rely too much on the software without thinking sufficiently carefully about the modelling task and how it is best done.

Particularly important as part of step 2 above is the need to think carefully about what the decision maker can do to adapt to bad or good outcomes as they unfold. Here too, imaginative thinking may be needed to find the realistic tactics to deal with the outcomes, especially bad ones. For an example of an analysis that included such tactical responses, see Kingwell *et al*. (1993). A failure to include such tactical responses in the analysis contributes to the over-estimation of the importance of risk aversion, discussed below.

Although artistry is unavoidably entailed at all stages in the analysis of risky choice, validation of the model developed is important to check that it provides a reasonable representation the actual problem (van Horn 1971; Sargent 2004). While there are a number of ways to approach this task, it is often a matter of reviewing and refining, as listed in step 5 above. Ultimately, of course, it is the decision maker(s) who must find the analysis credible; an essentially subjective judgment.

3. Expected utility and risk aversion

3.1 Choice of the best theory

The *Subject Expected Utility Hypothesis* (SEU), also know as *Bernoulli's Principle*, has a long and distinguished history (e.g., Bernoulli 1738; Ramsey 1931; von Neumann and Morgenstern 1944; Arrow 1951; Savage 1954). Basically, the hypothesis is that rational persons will seek to make risky choices consistently with what they believe, as measured by their subjective probabilities, and with what they prefer, as evaluated via their utility functions for consequences. The decision maker's utility function for outcomes is needed to assess risky alternatives since the shape of the utility function reflects an individual's attitude towards risk (Anderson *et al*. 1977, pp. 66-69). The SEU hypothesis states that the utility of a risky alternative is the decision maker's expected utility for that alternative, meaning the probability-weighted average of the utilities of outcomes.

The SEU hypothesis has been criticised because it has long been recognised that many people do not act consistently with the theory in certain risky choice situations (e.g., Allais 1984). The main critique has been the assumption about linearity in the probabilities (or equivalently, the independence axiom). Other axiomatic formulations (e.g., Kahneman and Tversky 1979; Quiggin 1993) have led to other more general theories that seem to model behaviour better. Recently, Rabin (2000) has shown that typical aversion to individual risky prospects with small losses is so great as to be inconsistent with any utility function expressed in terms of the utility of wealth. Such *loss aversion* implies *failure in asset integration*, meaning that people seemingly do not regard small gains and losses as changes in wealth (see, e.g., Binswanger 1981). Evidently the SEU hypothesis is flawed as a behavioural theory of choice (Rabin and Thaler 2001).

In prescriptive applications, however, it is clear that loss aversion is irrational because, by the operation of the law of large numbers, over many small risky prospects with better than fair odds, it implies forgoing the opportunity of profiting with negligible chance of loss. Moreover, loss aversion often disappears when people are given the opportunity of repeated choice or when the size of the risk faced is increased. Hence, for prescriptive decision analysis an assumption of rational preferences can be justified. Whatever may be our inclination, it makes sense to make most risky choices by regarding losses and gains as changes in wealth, which, after all, is just what they are. In other words, we should stick with the SEU hypotheses using a utility function for wealth if we want to act sensibly. So, we come to our third proposed principle:

Principle 3. Despite some limitations that have recently been given renewed prominence, the subjective expected utility hypothesis has yet to be displaced as the best model for normative decision analysis.

While the argument above in support of this principle is our own (as expounded also in Hardaker *et al*. 2004a, pp. 106-107), there is some consensus that, although alternative utility theories are more relevant in modelling behaviour, the SEU hypothesis remains the most appropriate theory for prescriptive assessment of risky choices (Machina 1987; Edwards 1992). Among agricultural and resource economists this view has been supported by Meyer (2001) and Just (2003).[3]

3.2 Difficulties in application of SEU hypothesis

While we believe the SEU hypothesis to be valid for prescriptive decision analysis, there are some significant difficulties in application. Although attempts have been made to elicit utility functions from relevant decision makers to implement the SEU hypothesis in the analysis of risky alternatives in agriculture (Robison *et al*. 1984), the results have often been rather unconvincing (King and Robison 1984; Anderson and Hardaker 2003). It seems that many people lack the introspective capacity to be able to respond consistently and convincingly to hypothetical questions about their risk attitudes (see, e.g., Huirne *et al*. 1997); a limitation that we suspect has sometimes been compounded by inept interrogation methods. Even when real money prizes have been offered (Binswanger 1981), it seems that loss aversion has led to results that are difficulty to put much faith in.

If direct elicitation of risk attitudes has proved tricky, attempts to elicit risk attitudes from observed behaviour also confront a number of problems. First, such studies can only assess the decision maker's risk attitude in the past, while decision analysis in concerned with evaluating future outcomes. Second, errors in model specification tend to be rolled into errors in the estimates of risk aversion coefficients, often causing over-estimates. For example, omission of some constraints in whole-farm programming models may lead to the attribution of diversification to risk aversion when it is really a response to technical considerations such as the need for crop rotations for soil health, the need to spread work loads, or the need for reasonably regular income flows. Third, it is usual to assume that the decision maker's probabilities about the uncertain events of concern were the same as those of the analyst, the latter typically being drawn from some historical data that may not relate well to the actual experience and expectations of the decision maker. For these or other reasons, some studies in the mould have found coefficients of risk aversion that seem hard to credit.

These considerations lead to our fourth principle:

Principle 4. Measuring the risk attitudes of decision makers is difficult and will give misleading results if based on inappropriate hypothetical or real choice situations or on inappropriate analyses of observed behaviour.

Note that we are not asserting that relevant measures of risk aversion cannot be obtained, but rather are flagging the need for more care in the way this task is tackled and for more

[3] In recent decades, fuzzy set theory (Zadeh 1965) has been given increased attention for problems with high degrees of imperfect and inconsistent information (Taylor and Zacharias 2001; Taylor 2003). The approach is not dealt with in this paper, but for interesting readers, applications of fuzzy set theory are given in, e.g., Cornelissen *at al.* (2001), Duval and Featherstone (1999) and Beynon *et al*. (2004).

caution in interpreting the results. We believe, for example, that it is often possible to elicit a reliable utility function for wealth from well-motivated and well-briefed decision makers.

Partly to avoid the need to elicit a specific single-valued utility function (or a single value for a coefficient of risk aversion), methods under the heading of stochastic dominance or efficiency criteria have been developed. Stochastic dominance criteria are useful in situations involving a single decision maker whose preferences are not known precisely and in situations where there is more than one decision maker, such as in formulating extension recommendations for a group of farmers. Stochastic efficiency methods, and particularly SERF (stochastic efficiency analysis with respect to a function) (Hardaker *et al*. 2004b), provide a general approach that is consistent with the SEU hypothesis and that narrows down the range of choice to an efficient set. Moreover, the simple principle of exploring the impact on risky choice of varying the assumed degree of risk aversion within a plausible range can be applied to almost any of the forms of risk analysis. That should surely quieten those critics of decision analysis who see problems in utility function elicitation as a main stumbling block.

On the other hand, there is a limit to what can be achieved by stochastic efficiency methods, so there is a continuing need for more work on how risk attitudes can be more reliably assessed. In this regard, Just (2003) has noted that elicitation of utility functions and estimates of risk attitudes have almost entirely focused on short-run problems. He argued that more research is needed on intertemporal risk attitudes, although just how that is to be done, given the difficulties noted above, is debatable. There is a similar case to be made that there has been too much focus on single-attribute utility functions when there exists ample evidence of the diversity of farmers' goals (e.g., Gasson *et al*. 1988; Bergevoet *et al*. 2004). Multi-attribute utility functions would also be useful in the analysis of risky choices in resource and environmental economics.

3.3 The importance of risk aversion in agriculture

Given the admitted difficulties in application of utility theory, how much importance should be attached to farmers' risk aversion in agricultural decision analysis? It is easy to find studies that imply that farmers' are very risk averse, even for quite marginal decisions. Some of these studies have been based on brave assumptions about the degree of risk aversion, often without explicitly saying what has been assumed or done. In contrast, some later studies have shown that the cost of ignoring risk may be small, at least for farmers' partial or short-term decisions (e.g., Pannell *et al*. 2000; Lien and Hardaker 2001).

Reasons why the importance of risk aversion has been exaggerated include:

1. too narrow analysis that ignores interactions with other activities and options on- and off-farm, including risk-sharing options and possibility for tactical or sequential adjustment; and
2. over-estimates of decision maker's degree of risk aversion due to inappropriate elicitation of utility functions inducing loss aversion, or to biased estimates from studies of observed behaviour, both of which have been discussed above.

Support for the above assertions may be found in, for example, Musser *et al*. (1986), Pannell *et al*. (2000), Meyer (2001), Just (2003); Hardaker *et al*. (2004a, pp. 86-89) and Malcolm (2004).

The omission from the analysis of the possibility to respond tactically when events unfold (embedded risk) can lead to over-estimation of the importance of bad outcomes (Antle 1983; Pannell *et al*. 2000). Moreover, at least in more developed countries where access to credit is easy, most farmers with reasonable equity can readily ride out normal year to year variations in income flows (Just 2003).

Assuming that asset integration makes sense, the decision maker's utility function for wealth is the appropriate one for prescriptive analysis. Risk aversion can be described by the absolute and relative risk aversion functions for wealth (Pratt 1964; Arrow 1965). Moreover, Arrow (1965) suggested that the value of the relative risk aversion function for wealth is not very far from one, and it seems likely that it is seldom above about four (Anderson and Dillon 1992). Then it is possible to derive estimates of the plausible range of absolute risk aversion coefficients for a range of assumptions about size of risk relative to wealth. Using such an estimated range, Hardaker *et al*. (2004a, pp. 113-118) show that, for capitalist farmers, risk aversion, though not negligible, is likely to be of small importance in affecting farmers' partial and short-term decisions.

All this leads us to our fifth principle:

Principle 5. The importance of risk aversion has generally been exaggerated, especially in the context of farmers' partial or short-term decision making in more developed countries.

The implication of this principle is that for many farm management decisions, it will be adequate to base choice on maximising expected money value. For cases where that seems a too strong assumption, the handling of risk aversion depends on how the problem is cast and hence on how the consequences are measured. Hardaker *et al*. (2004a, pp. 110-113) show how to get better consistency of risk aversion across payoff measures. For example, the coefficient of absolute risk aversion with respect to temporary income will usually be about the same as the coefficient of absolute risk aversion with respect to wealth. However, it is not correct to apply the coefficient of relative risk aversion for wealth to the assessment of risky temporary income.

Note that we do not assert the risk aversion never matters. It is likely to be important for asset-threatening decisions, e.g. major investments, since, by definition, these will have a larger impact on the decision maker's wealth than partial or and short-term decisions. For very poor farmers in less developed countries, even quite small risks may matter a lot. The general rule, however, is that it is the risks that threaten a farmer's long-term asset base that really matter (Just 2003).

3.4 Risk aversion and public choice

Dealing with risk in public choice, in principle, merely involves application of the same methods as for private decision makers. Thus analysis for public decision support should, for example, take into account any possible downside risk, and should include consideration of ways to deal with bad consequences if and when they eventuate.

The need for proper *ex ante* appraisal of public choices raises the issue of what utility function should be used in such analyses. In the case where all the consequences of the policy choice are adequately measured in money units via some form of benefit-cost analysis leading to a distribution of a measure of worth such as net present value, Arrow and Lind (1970), in a seminal analysis of public investment under uncertainty, argued that society is usually able, at least potentially, to pool its risks across the whole population. Consequently, they argued, society as a whole should be neutral towards risk. This view supported that of Samuelson and Vickrey (1964).

Cases that Arrow and Lind (1970) say are exceptional do, however, occur. They relate mainly to risk in project appraisal in less developed countries and deserve brief comment here. Little and Mirrlees (1974, p. 316) outlined when something other than the maximisation of expected net present value would be appropriate. Briefly, when a public project is large relative to national income, when project returns are highly correlated with such income, or when a particular disadvantaged group is involved, there is a strong case for explicit accounting for the riskiness of alternative actions by use of an appropriate risk-averse social utility function.

So we present our sixth principle:

Principle 6. For policy decision making, it is usually appropriate to assume indifference to risk because society can potentially share bad consequences among a very large number of citizens.

This principle should surely not be contentious. That is not to say, of course, that it is always followed. Politicians or public servants may choose to make such decisions in quite risk-averse ways if they fear that a bad outcome will adversely affect their chances of re-election or of advancement of their careers. But at least professional analysts advising on such decisions should avoid the temptation to be too conservative. For a discussion of the appropriate risk deduction in public project appraisal, see Anderson (1989).

4. State contingent approach

The state contingent approach (Chambers and Quiggin 2001, 2004) is an important theoretical development that should lead to improved methods of risk analysis, particularly, we suspect, in econometrics. In this latter connection, Just has proposed the following principle (Just 2003, p. 140, principle 9):

'If the expected utility hypothesis holds, then the relative advantages of the state-contingent versus parametric distributional representations of risk depend on a comparison of the number of states of nature versus the number of distributional moments required for the adequate representation of the producer's stochastic problem.'

We believe that this principle does not do full justice to the state contingent approach as propounded by Chambers and Quiggin. In particular, Just seems to believe that the state contingent approach depends on the validity of the expected utility hypotheses, whereas Chamber and Quiggin indicate that the underlying preference structure can be much more general. However, in so far as the approach is based on specifying the outcome of some risky choices contingent upon the state of nature that eventuates, it is quite familiar to prescriptive decision analysts. Leaving aside work with an econometric orientation, and some mathematical programming studies, it usually proves more expedient to do decision analysis in terms of discrete states of nature rather than in terms of distributions of outcomes defined in terms of (moments of) continuous distributions.

Chamber and Quiggin, however, do much more than this. As we understand it (and we do not find it easy going), they show how adopting a state contingent form of analysis allows risk to be incorporated into the conventional theory of production, rather than being treated as a modification thereof, as was propounded, for example, in the classical work of Magnússen (1969). In particular, with the state contingent approach one is able to use the dual formulation of optimal operating conditions to encompass risk and its consequences. Rasmussen (2003, 2004) used the approach to derive criteria for optimal production under uncertainty. He has elucidated the conditions under which a risk-averse decision makers will use more or less input than if they were risk neutral; information that he argues is useful in both descriptive and normative work.

How this undoubtedly important development might affect the ways that the analysis of risky choice will be implemented in the future remains to be seen. Only now is empirical work based on this approach in agriculture and resource economics beginning to appear (J. Quiggin, pers. comm. 2005), all so far of an econometric nature. We are not aware of any applications of the theory to date in a predominantly prescriptive setting, so we are currently doubtful whether the approach will prove very useful for applied normative studies in agriculture and resource economics. In this circumstance, and in view of our lack of confidence in predicting how state contingent theory may be developed and applied, we think it best that we do not attempt to specify any principles relating to it.

5. Probabilities for risk assessment

As indicated earlier, our treatment of this topic is founded on our view that all probabilities are subjective statements of degrees of belief in propositions about the world. We recognise that this view is not accepted by many, perhaps most, agricultural and resource economists. However, this is not the place for missionary zeal to try to covert the unbelievers. Instead we ask the uncommitted or unsure to consider the following points:

1 The notion of probabilities as subjective has been supported by some distinguished thinkers. The theory is based on reasonable axioms and sound logic, and there exist well-tried methods of implementation (e.g., Ramsey 1931; de Finetti 1964, 1972, 1974; Savage 1954, 1971; Staël von Holstein 1970, 1974).
2 The notion of deriving probabilities from relevant, reliable and reasonably abundant relative frequency data is entirely consistent with the subjectivist view.
3 Rejection of the notion that subjective probabilities can have meaning implies that no systematic analysis is possible to support most of the important risky choices faced by farmers, resource managers, policy makers and, indeed, everyone.

The necessity for and appropriateness of subjectivity in decision analysis has found wide acceptance (e.g., Raiffa 1968; Anderson *et al*. 1977; Morgan and Henrion 1990; Wright and Ayton 1994; Clemen 1996). As long ago as 1951, Arrow wrote that 'the uncertainty of the consequences […] is basically that existing in the mind of the chooser'.

5.1 Sparse or zero data situations

When there are abundant data that are relevant and reliable, the subjective and relative frequency views of probability will usually coincide. However, it is not always recognised that accepting probabilities drawn from some historical data set involves a subjective belief that the historical data are relevant to the future period when the uncertainty being modelled for decision analysis is revealed. In other words, adopting probabilities based on historical data involves an explicit yet seldom examined assumption of stationarity. The subjectivist is more likely to question this assumption while the objectivist will usually be obliged to adopt it willy-nilly.

More usually, the difference between the two main contending views of probability occurs when data are sparse or absent. Then rejection of the essentially subjective nature of choice can lead to some unfortunate mistakes, e.g., use of inappropriate but available data, ignoring the most important problems or variables for lack of historical data, use of cross-section data to reflect uncertainty over time, etc. (Watson and Anderson 1977; Taylor and Zacharias 2001; Just 2003, p. 153). Yet in the analysis of many important risky decisions the all-too-familiar situation is one in which abundant and relevant data are neither available nor obtainable at reasonable cost.

If data are sparse or absent, the subjectivist will seek to use the best obtainable probability judgments about important uncertain variables to allow analysis to proceed, whereas the objectivist or frequentist can do nothing, which is surely unsatisfactory.

The above discussion leads to us our next principle:

Principle 7. Abundant, comprehensive and relevant data are often not available or obtainable for many important risky agricultural decisions. As a result, analysis must often be based on subjectively assessed probabilities.

The implications of acceptance of this proposition are far-reaching, extending far beyond the scope of this paper. However, we have sought only to draw out some implications for applied decision analysis in what follows.

5.2 Making good probability judgments

Of course, subjective probabilities are not any old numbers that come to mind. First, they must be numbers that obey the usual rules of probability theory. Moreover, they should be consistent with what the decision maker (or the decision analyst acting for that person) really believes about the uncertainty to be faced. Thinking rationally about probabilities means striving for consistency in one's whole network of beliefs. So, for example, if some quantitative or qualitative information is believed to be relevant to the assessment of the probability of some uncertain event, the assigned probability should reflect the belief in that information.

More generally we propose the following related principle:

Principle 8. All probabilities for decision analysis should be thoughtfully and transparently obtained using the best available information, advice and well-considered and disclosed methods.

This means that possible sources of information should be considered and evaluated as to their suitability in supporting the formation of probability judgments. Sometimes there are no existing useful data and none can be collected. For example, this usually will be the case for risks that have not yet been experienced. Then probability assessment comes down to wholly subjective judgments by the decision maker (or those assisting for that person). If there are some data already available, they need to be carefully evaluated to assess their relevance, reliability and applicability to the assessment task at hand. As discussed below, particularly when data are sparse or suspected to be biased in some way, the raw numbers will need to be combined with some subjective judgments before they can be used. In the following sub-sections we deal in more detail with the two cases of no data versus some data.

Whatever is to be done in assessing probabilities, it is generally important to make the process as transparent as possible - always tell what you did (Morgan and Henrion 1990, ch. 3). The case for transparency in public decision analysis is obvious, but even in private decisions, documenting what was done and assumed facilitates later review and offers greater opportunities to learn from past failures and successes. It seems to us that too much published work in agricultural and resource economics is based on probability assumptions that are inadequately documented and justified. We suspect that this deficiency comes from the fallacious belief that probabilities must be relative frequencies. When, perforce, they come from dubiously appropriate data, authors may feel under pressure to 'paper over' the deficiencies to satisfy editors and reviewers.

5.3 Subjective elicitation of probabilities

The subjective assessment of the probabilities for some decision problems usually needs to start with clarification of the nature of the uncertainty to be faced. This process, which may take some considerable time and thought, may be assisted with the use of influence diagrams or probability trees (Clemen 1996). Once the preliminaries are over, several techniques have been proposed for the elicitation of subjective probabilities, such as the equivalent lottery method, visual impact methods and fractile methods (e.g., Hardaker *et al*. 2004a; Morgan and Henrion 1990, ch. 6; Clemen 1996).

The chief difficulty with any such methods is the problem of bias in subjective probability assessments. There is substantial evidence in the psychological literature of the various types of error that people typically make in such assessment tasks (see, e.g., Plous 1993 for a comprehensive review or the summary in Hardaker *et al*. 2004a, pp. 86-91). These include over-confidence in one's judgment (leading to too tight distributions), avoidance of uncertainty, misconception of chance, anchoring problems, and problems due to motivational incentives. On the other hand, there is rather little research (and almost none in agricultural and resource economics) on how to overcome these problems. However, asking subjects for reasons and getting them to construct careful arguments in support of their judgments appear to reduce bias and improve the quality of the assessments (Morgan and Henrion 1990).

Another method that has been used, seemingly with some success, is the training of assessors with use of scoring rules. The procedure is to reward assessors who assign distributions to almanac-type questions in such a way that the total expected score is maximised by assigning probabilities consistently with what they really know about the uncertain questions posed. Marks are awarded using a *proper scoring rule*, which is one such that assessors maximise their expected scores if they report their true beliefs (e.g., Savage 1971; Matheson and Winkler 1976; van Lenthe 1993). The rewards may be in the form of valuable prizes or, more usually, merely the satisfaction of doing well, perhaps in comparison with others, and from improving one's own performances with gained experience.

With so little empirical evidence on how to minimise bias in subjective probability assessments, it is impossible to be confident about what is best. However, we tentatively propose the following principle:

Principle 9. In obtaining subjective probability assessments for risk assessment, analysts should give careful thought to clarification of the nature of the uncertainties to be faced and to ways to motivate and assist assessors to minimise bias in their judgments.

In this context, we also flag the need for more research to calibrate probability distributions obtained from farmers or others using different elicitation methods with a view to improving the guidance that can be offered to analysts about how best to proceed. Calibration of probabilities is discussed further below.

Some bias in probability assessment appears to arise from a failure of imagination. This may be very important when assessing low probability events. Hence it may help to 'brainstorm' to bring into mind a more complete set of possible futures. Had this been done in relation to the risk of tsunamis in the Indian Ocean, the now proposed warning system might have been in place before the recent disaster struck. But perhaps that is unfair because there is a particular difficulty in probability assessment in relation to rare events that have very serious consequences. Almost by definition, there are few or no data available for such events. There is also evidence that people may not even want data on the probability of an extreme event occurring (Kunreuther 2002). The assessment difficulties appear to arise from two causes. First is the failure of imagination already mentioned. If an assessor has had no experience of a particular outcome, he or she may have difficulty in imagining it could occur. For example, few people had imagined a terrorist attack on the scale and using the methods of September 11th. Even if an event can be conceived, it is obviously difficult to assign a meaningful probability to it when it has hardly ever or never happened before. The second problem arises because of the difficulty people have in discriminating between very small probabilities. A chance of one in a thousand may seem not much different from a chance of one in a million, yet the implications for risk management of the difference between the two can be very great. Experiments have shown that people can get a better grasp of low probabilities if they are related to familiar scenarios described is realistic detail (Kunreuther *et al*. 2001).

5.4 Use of experts

Normally the decision maker’s personal probabilities are the ones that should be used in decision analysis, but in cases where that person is not well informed about the risk to be faced, it obviously makes sense to seek expert advice. Use of experts may be particularly apposite in public decision making. Moreover, if it makes sense to consult one expert, it seems obvious that it would be better still to consult several, provided that each brings some unique insights to the problem at hand. Our next principle, therefore, is:

Principle 10. In cases where data are sparse or absent, it will be wise to seek probability assessments from people with relevant expert knowledge. Moreover, provided the assessments are made independently, using multiple experts is likely to give better results than consulting only one.

For a comprehensive discussion of the topic of use of expert opinion in forming subjective probabilities, see Cooke (1991).

The proviso about the need for independence provides a clue to answering the questions of how experts should be selected and how many should be used. The aim should be to pick people who are knowledgeable about the risk to be faced but who come from different professional backgrounds or who have had different experiences of the world. Moreover, there is likely to be diminishing returns from expanding the number of experts called upon in that the criterion of reasonable independence will become harder to fulfil as the number is increased. While there is no hard and fast rule, perhaps four or five will usually be a reasonable number.

The use of a number of experts leads to several questions. It is sound practice to try to understand why the different experts assign different probabilities to the same events. If there are fundamental and inconsistent differences between experts, it may be inappropriate to combine their different opinions since to do so may produce an ‘average’ distribution that is meaningless (Morgan and Henrion 1990, pp. 164-168). But then more inquiry will be needed to try to resolve the issue. Normally, however, it will make sense to combine the assessments of the different experts into the single probability distribution(s) needed for analysis. The problem is to decide how. A number of methods have been proposed and there is some uncertainty about what is best (Clemen and Winkler 1999). There is general agreement that it usually makes sense, when possible, to start by pooling information among the experts to try to reduce differences between them in their perceptions. On the other hand, this process can introduce bias unless it is done carefully. Getting the experts together to share ideas may seem sensible, but there is clear evidence that this can be dysfunctional. For example, sometimes the group dynamics seem to work to produce a much more extreme and more over-confident assessment than any of the individuals would have suggested alone. This effect, known by the unfortunate name of ‘group think’ was blamed for some of the most serious intelligence failures that preceded the recent invasion of Iraq. Other types of dysfunction may occur, for example, when one strong-willed or high-status but ill-informed individual is able to dominate the group.

These sorts of problems led to the development of forms of information sharing followed by reassessment in which the anonymity of the individual group members is preserved. The best know of these methods is the so-called Delphi method, which has found reasonably wide application (Linstone and Turoff 2002). These considerations lead to our next proposed principle:

Principle 11. Sharing information among assessors makes sense, so some form of feedback and reassessment has the potential to yield better probability assessments. However, analysts should generally seek to use group methods with feedback that are less likely to be dysfunctional, such as the Delphi method.

5.5 The consensus problem

Getting experts to share information can be expected to lead to some convergence of views in most cases. However, a complete consensus will rarely be achieved unless the members are allowed to meet and to work out for themselves a way of resolving their differences. As noted, that is usually not a good idea. Consequently, the analyst is left with the problem of how to combine different probabilities (or probability distributions) from the different experts. This problem has attracted considerable attention in the literature.[4] According to French (1985), several procedures have been proposed, some on pragmatic grounds and others justified axiomatically. A number of impossibility theorems have been advanced, but then disputed. However, apart from behavioural methods, such as the Delphi method, two main options seem to be dominant these days. First is the use of some form of weighted average of the individual distributions. Several different weighting schemes have been proposed, with the best usually being weights assessed according to the past performance of the experts in similar assessment tasks (e.g., Clemen 1989; Clemen and Winkler 1999). Second is the use of Bayesian methods. Although these have considerable appeal in logic, there are operational problems relating chiefly to the difficulty in obtaining appropriate likelihoods. On the other hand, Jouini and Clemen (1996) have proposed an innovative approach to Bayesian aggregation in which dependence among sources is encoded into a copula. However, experimental evidence seems to suggest that forming averages of experts' distributions often works about as well as more sophisticated methods (Clemen and Winkler 1987) so, by recourse to Occam's Razor, that may be the best choice till something superior is discovered.

Since the consensus problem is still not fully resolved, we choose not to advance any principle relating to it. Instead, we urge that analysts should become acquainted with the pros and cons of different existing methods, as reviewed by Clemen and Winkler (1999), and should keep an eye open for new developments.

5.6 Feedback to improve probability assessment

For events that occur repeatedly, it is possible to match an assessor's subjective probability judgments against observed relative frequencies. For example, if, on a number of occasions, an economist has specified a 30% chance that the world price of wheat will rise in the coming period, wheat prices should have subsequently risen on about 30 per cent of those occasions for the forecasts to be well calibrated. If this is not the case, the forecaster needs to look to his or her laurels to do better in the future. Poorly calibrated (unreliable) probability assessments imply some significant bias that should be corrected. See Morgan and Henrion 1990, ch. 6 for a review. We therefore propose the following principle:

Principle 12. Whenever possible, subjective probabilities should be calibrated against actual outcomes so that assessors can be given feedback on their performance with a view to improving the reliability of their assessments.

[4] The size of the literature on the consensus problem is indicated by the fact that a Google search for 'combining probabilities experts' produced about 53 000 hits. We have discovered almost no publication in agricultural and resource economics that deals explicitly with this important issue.

Assessed discrete probabilities can be plotted against actual frequencies to yield a calibration curve. The curve for a well-calibrated assessor should be close to the diagonal. Assessors have a tendency to be overconfident, so the probabilities tend to be too near certainty (0 and 1) on the calibration curve. Although feedback and training of assessors can be arduous, it should be useful, even essential, in fields such as economic and weather forecasting (Murphy and Winkler 1977). Moreover, the more such studies are reported, the more we can learn about types and sources of bias in probability assessment, increasing the opportunities to minimise or avoid these problems.

5.7 Using data in probability assessment

We now turn to the situation where there some data available upon which to base the assessment of probabilities. In this case, it is important first to consider the reliability and the temporal and spatial relevance of the data to the assessment of the uncertainty at hand. How many observations are there? How were they obtained and by whom? What, if anything, was done to verify and validate the data? If the data were a sample, how representative are they of the population from which they were drawn? How large were errors in collecting and reporting the data likely to be? Is the stationarity assumption justified? Were the data collected on the farm or for the environment for which the decision analysis is to be performed? Or did they come from some location perhaps quite far away? If the data are likely to be biased for any of these or other reasons, ways to try to correct for such bias should be considered and, if possible, applied. In the wost cases it may be best to discard misleading information and to use more subjective assessments as described above.

It is obvious that basing probability assessment on dubious data alone is not rational. Hence, we suggest the following principle:

Principle 13. Sparse or suspect data should only be used for decision analysis in combination with a careful assessment of their relevance and of how to accommodate the imperfections of the data.

We wonder how often the above-mentioned questions are considered in professional studies. Certainly, some data 'laundering' goes on, chiefly discarding outlying observations that would otherwise spoil goodness of fit or significance statistics. How often these manipulations are unreported it is impossible to know. Obviously, we advocate much more transparency in such matters.

Any measurement can be regarded as a sum of the true value, systematic error (measurement bias and sampling bias), and sampling error (e.g., Schlaifer 1959, ch. 31). The sample selection method is crucial to minimise the systematic error. There are weighting and frequency procedures that can be used to reduce sampling bias. However, estimating the possible magnitude of systematic error is difficult and of necessity involves a large element of subjective judgment.[5]

Ideally, samples should be validated against the population for main characteristics related to the ones of interest for the decision analysis. There is a tendency to underestimate the effect of little-known sources of error so that the existence of systematic error may not be recognised (Morgan and Henrion 1990, ch. 4). A typical example on sampling bias is use of experimental yield data in farm analysis. Response under experimental conditions will in general significantly exceed the response achieved under workaday farm conditions (Davidson *et al*. 1967; Dillon and Anderson 1990). Historical time-series data should normally be adjusted for inflation, and technological change may cause a need for trend-

[5] Of course, we do not regard the fact that subjectivity is involved as a reason not to attempt correction.

adjusted data (Hardaker *et al*. 2004a, ch. 4). If there are known and predicable causes for irregularities in the process generating the data, obviously these should be taken into account.

Agricultural production is highly fragmented and heterogeneous, yet many statistics are only available at some level of aggregation. As Just (2003) stresses, farm-level analyses should be based on micro-level data, so there is a need to collect panel data over several years. Such data are generally essential for a thorough analysis and calculation of probabilities for the serious risks that farmers face. Presumably, it is the lack of such micro-level time-series data that has led some researchers into the error of using aggregated data to assess risk at the individual farm level (Just and Weninger 1999).

5.8 Smoothing of empirical distribution

In cases with sparse data, or even when the data are relatively abundant, it usually makes sense to smooth out any irregularities in the distributions. The case for smoothing lies in the fact that a single observation of some continuous uncertain variable is made up of a predictable or deterministic component plus or minus a stochastic deviation. The irregularities in an empirical distribution are a result of sampling from the true distribution and thus reflect sampling error. On the other hand, it is almost always reasonable to assume that the population follows a smooth distribution, implying that the irregularities should be eliminated in fitting the distribution (Schlaifer 1959, 1969; Anderson 1974; Anderson *et al*. 1977).

Smoothing can be done assuming that the marginal cumulative distribution function (CDF) of some continuous uncertain quantity will be a smooth curve, typically but not always sigmoidal (Anderson 1974; Anderson *et al*. 1977, ch. 2; Clemen 1996; Hardaker *et al*. 2004a). Hence it makes sense to smooth out the irregularities typically found in even relatively large samples, and the smaller the number of observations, the greater the need for smoothing (Whittle 1957).

Before any smoothing is attempted, all supplementary information that can make the process more trustworthy should be considered, especially when the data are sparse. For example, it will usually be reasonable to assume that the upper and lower bounds of a probability distribution will be more extreme that those observed in a small data set. Often expert judgments can be used to get estimates on such bounds and perhaps also an estimate of the modal value (Vose 2000).

There are several options to smooth probability distributions from data. One option is to plot the data points using the rule that the k-th ranked observation is an estimate of the $k/(n+1)$-th fractile, then to draw a smooth curve approximating these points by hand (Schlaifer 1959; Hardaker *et al*. 2004a, pp. 69-71). Or non-parametric methods can be used to estimate a smoothed empirical CDF, such as spline and kernel methods (e.g., Whittle 1957; Silverman 1986). A third option is to fit a theoretical distribution to the data (e.g., Feldman *et al*. 2004; Vose 2000, ch. 9; Hardaker *et al*. 2004a, ch. 4), and there exists software such as BestFit and Simetar to do this. Although distribution fitting may be preferred by some as ‘more objective’, our preference is usually for some method of non-parametric smoothing. This is because we believe that it will often be unsafe to assume that an uncertain quantity of interest conforms to some convenient parametric distributional form. Moreover, especially if the risk is concentrated in one of the tails of the distribution, some tests of goodness of fit of fitted distributions may be unsatisfactory.

If the CDF is to be smoothed, hand smoothing may be argued to give the best opportunity to incorporate additional information about the shape and location of the distribution, but other more formal methods may be preferred in some cases. For example, in a simulation model Lien *et al*. (2004) used a multivariate kernel density estimator to smooth sparse input data.

5.9 Collecting more information to supplement sparse data

When data for probability assessment are inadequate, it makes sense to consider collecting more information. Two options should at least be considered: collecting more empirical data or seeking probability assessments from experts, as discussed above. There is evidence of the human tendency to limit the amount of information sought or used in choice, especially for problems where imagination is difficult (Morgan and Henrion 1990, ch. 6). These considerations lead us to Principle 14:

Principle 14. When data for probability assessment are inadequate, more data should be collected whenever this is possible and justified.

Before taking steps to collect more information, one should be sure that the necessary information really is not available from other sources. Then it is a matter of comparing the expected value of the new information with the likely costs of collection (including the costs of delay). In principle, Bayesian *preposterior analysis* can be used to determine the expected value of collecting more information (e.g., Anderson *et al*. 1977; Clemen 1996, ch. 12), even though it is often difficult in practice to do the calculation. However, an informal benefit-cost analysis of collecting more information can always be done. That analysis should take account of the difficulties and pitfalls in data collection, especially problems with social surveys (Pannell and Pannell 1999).

5.10 Revision of probabilities

The aim in collecting more information for decision analysis obviously is to be able to make better probability judgments. If the new data amount to an increase in the size of sample, they can be added to the existing data and the analysis can proceed as outlined under 5.8 above. However, in other cases the analyst is faced with the task of making use of data of different types or from different sources. The danger in this case is that, as psychologists have shown, most people exhibit *conservatism* in this task, meaning that they do not revise their prior probabilities sufficiently in the light of the new evidence (e.g., Peterson and Beach 1967). At least in some cases, Bayes' theorem can be used to overcome this problem, since it ensures that full weight is given to any additional information that becomes available (Anderson *et al*. 1977). Hence, we propose the following principle

Principle 15. When possible and appropriate, Bayesian methods should be used to update prior probabilities in the light of new evidence.

The essential feature of Bayes' theorem is that it provides a logical mechanism for consistent processing of additional information. Bradford and Kelejian (1978) have show how Bayesian updating can improve the quality of information used to construct forecasts of wheat prices. Kristensen (1993) illustrated how Bayesian updating can be applied in dynamic programming. However, one common problem in the application of Bayesian updating is how to get the likelihood probabilities. These measure the reliability of the additional information. If there is no empirical evidence on which to base the likelihoods, they may be have to be subjective judgments. In that case, it may be as easy to assess the posterior probabilities directly, although a Bayesian calculation may still be useful as a cross check.

5.11 Dealing with stochastic dependency

Most decision problems involve more than one stochastic variable. It is easy to show empirically that if stochastic dependency between two or more variables is ignored for the sake of ease in modelling, the distribution of the output variable(s) may be seriously in error. Hence, we propose the following principle:

Principle 16. Stochastic dependency among uncertain input variables often matters in affecting the distribution of consequences. Omitting dependency in analysis may lead to erroneous results.

The problem with stochastic dependency is that it seldom easy to assess and it can be even harder to model effectively in the analysis. As a result, it is all too common to find that dependency has been assumed away, or, if accounted for at all, linear correlations are assumed to represent what is happening adequately, usually applied in conjunction with the assumption of a multivariate normal distribution. In reality, the dependency between uncertain variables may differ at different levels of those variables, and, as empirical findings show, the assumption of normal distributions for many agricultural phenomena is much less likely to be a good representation of reality than its ubiquitous adoption suggests (e.g., Anderson 1982; Ramirez *et al*. 2003). Assuming normal distributions inappropriately may lead to serious errors in the tails of the distributions where often the most serious risks occur (e.g., insurance and derivative instruments, food safety risk, and environmental risk). If the marginal distributions are not assumed to be normal (or lognormal), it is usually possible to draw correlated samples in Monte-Carlo simulation accounting only for rank correlations (not the more familiar linear product-moment correlations). Again, because rank correlations do not tell the whole story about stochastic dependency (and, in fact, also measure only linear dependency), the sampled values may be a poor representation of the 'true' stochastic dependency.

There are, of course, circumstances in which dependencies can legitimately be ignored, for example if the dependency is weak, or it is between variables with little influence on the output variables of interest (Smith *et al*. 1992). Techniques helpful to determine whether it is necessary to model dependency are discussed in Vose (2000, ch. 11) and Richardson (2004, ch. 7).

When dependency has to be addressed, a number of methods are available. For example, if abundant relevant data are available, either the data can be allowed to 'speak' by using the historical information as direct input to some stochastic simulation, or, in some cases, appropriate statistics can be obtained to define the joint distribution incorporating the dependencies between variables. But unfortunately, abundant data are more the exception than the rule, and commonly at best only sparse data are available. In cases with sparse or no relevant data, some methods have been proposed for the subjective assessment of joint probability distributions (Fackler 1991; Clemen and Reilly 1999; Hardaker *et al*. 2004a, p. 172). But eliciting peoples' beliefs about joint distributions is a demanding task, especially for more than two variables (Morgan and Henrion 1990, ch. 6).

A second approach is based on the notion that, if the dependency is real and not a statistical artefact, there must be underlying causal factors at work. If these can be identified and their distributions and effects quantified, the cause of dependency can be modelled. Burns and Clemen (1993) suggest the use of influence diagrams for this purpose. Hardaker *et al*. (2004a, pp. 82-86) call the method the *hierarchy of variables* approach. Of course, a common problem with this approach is lack of data. For example, crop yield may be a function of a range of variables, such as soil conditions, rainfall, temperature, use of seeds and fertilisers, field work and timing, harvesting technique and timing, etc. Even using all the best information and advice, it will seldom be possible to model all causal factors and their effect on crop yield, so a decision must be taken about what can be a 'good enough' representation of the causality.

The conditional distribution method is another procedure that has been used to tackle the problem of appropriately modelling multivariate non-normal probability distributions for simulation and other types of risk analysis. Gelman and Speed (1993) discuss the combination of marginal and conditional distributions that suffice to determine a joint distribution. Taylor (1990) illustrates this approach as one of the two procedures described in his paper. However, if one variable depends on many other variables (so that many conditional probabilities are required) the procedure is not very operational.

In recent years copula methods have become increasingly popular, especially in finance, as tools to describe and simulate multivariate distributions (Cherubini *et al*. 2004). Given two or more marginal distributions, the copula function describes how they 'come together' to define the multivariate distribution. Since the copula function separates out the dependence structure from the marginal distribution functions, any types of marginal distributions can be joined together into a joint probability distribution. Moreover, once specified, the copula allows for Monte Carlo sampling from the implied joint distribution.

There are many different copulas to choose from (Nelson 1999). Some of the copulas better account for the dependency in the tails of the stochastic variables than others. Copulas are estimated statistically from a data set, so the method can usually only be applied when abundant data are available.

In the agricultural and resource economics literature, application of copula methods to account for dependency between stochastic variables is limited. Richardson and Condra (1978), Ramirez (1997), King (1979), Taylor (1990), and Richardson *et al*. (2000) all used normal (or Gaussian) copulas in their models to account for stochastic dependency. However, none of these studies used the full power of copulas to join non-normal distributions, suggesting that there is a need for more research on the scope for use of copulas in applied risk analysis in agriculture and resource economics.

Another little used approach in decision analysis in agriculture is bootstrapping (Elfon 1979). The bootstrap method together with look-up functions such as exist in Excel can be used to simulate a multivariate empirical distribution. Bootstrap simulation of multivariate distributions maintains the correlation between variables and in addition the higher-order moments characteristics of the variables (Richardson 2004). When sparse data exist, some smoothed bootstrap simulation procedures can be done (Elfon 1979; Silverman and Young 1987).

Finally, for a review of some further methods of dealing with dependency, see Biller and Ghosh (2004).

6. Concluding comments

As stated in the Introduction, the aim of this paper is to stimulate thinking and debate about how decision analysis can be done better in agricultural and resource economics. Our list of principles may be contentious. We welcome criticism and suggestions for improvement. It is our hope that these ideas will challenge some established practices that we think are misguided, even wrong. We think it is time for members of the profession to stop hiding behind the disguise of supposedly respectable 'objectivity' and to be more honest about the many subjective judgments that inevitably have to be made their work. It is time for the profession to recognise that thoughtful and transparent subjectivity in not only 'OK', but is the only logical basis, at least for the analysis of risky decisions in agriculture and natural resource economics.

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