Supplement to Agrekon

Vol. 21 No. 2 October 1982

FUNDAMENTAL ASPECTS OF RISK AND UNCERTAINTY IN AGRICULTURE*

by J.B. Hardaker

Imperfect knowledge arising mainly from unpredictable variability leads inexorably to risk in agricultural decision making. Rational choice under risk is choice consistent with the decision maker's beliefs about the uncertainty he faces and with his preferences for possible consequences. Beliefs can be measured as subjective probabilities. Rationality also requires consistency in subjective probability judgements. Preferences can be encoded via Bernoullian utility functions. An optimal risky decision is defined as one that maximises the decision maker's subjective expected utility (SEU). The SEU model may be used in both prescriptive and descriptive analyses of risky choice. Prescriptive analyses can be useful in both farm-level and policy-level agricultural decision making under risk. Descriptive analyses may be useful to policy makers and others who need to try to understand and predict farmers' behaviour.

KNOWLEDGE, UNCERTAINTY AND RISK

In any decision there comes a moment of truth when a choice must be made. This 'decision moment' partitions time into the past and the future relative to the decision. In the past lies all the evidence that might be used to guide choice. The consequences of the decision, however, lie in the future and depend not only on the choice made but also on events that have not yet occurred. At least for decisions of any practical significance, the outcomes of the pertinent future events cannot be known with certainty at the decision moment. For example, when choosing between two possible crops, a farmer cannot know the weather conditions that will prevail in the coming growing season and that may significantly affect the crop yields.

Perhaps if we knew enough about the processes that determine the outcomes of future events we might be able to predict these outcomes with certainty. However, for better or for worse, the complexity of Nature (and hence of the man-made systems that are designed to exploit Nature) is so great that it is beyond human capacity to understand all Nature's processes perfectly. Thus, despite many years of study, we understand only to a limited extent the system that determines weather - certainly not well enough to predict very far into the future with any confidence. Economic forecasting is perhaps even more difficult than is forecasting based on the biological and physical sciences. Our ignorance of the future is compounded by the variable and unpredictable nature of the world we live in. These uncertainties have important effects on agriculture and influence choices made by farmers and other agricultural decision makers.

Following Knight (1921), some authors have distinguished two types of imperfect knowledge - risk, when the probabilities of the uncertain outcomes are known, and uncertainty, when they are not. However, the distinction is of little practical use and is discarded by most analysts today.[1] Probabilities can be 'known' in the sense implied by Knight only for stationary stochastic processes, i.e. for those sorts of events where there is variability but where the sources and nature of the variability remain constant through time. Such processes are rare in practical decision making. When they do occur it is not always possible or worthwhile to collect sufficient observations to allow the relative frequencies implicit in Knight's concept of risk to be calculated reliably. For example, rainfall is often regarded as a stationary stochastic process, which it obviously is not, in view of the long-term changes in climate that have been documented. Even disregarding this difficulty, it is not always possible to have a long series of site-specific rainfall observations to aid decision making.

In this paper Knight's distinction between risk and uncertainty will not be used. Instead, the two terms will be used more or less interchangeably. However, some distinction can be drawn based on common usage. Uncertainty may be used to describe imperfect knowledge about the outcome of some future event, while risk is used to refer to imperfect knowledge about the consequences of a decision. This is more or less consistent with the *Concise Oxford Dictionary* definition of risk as 'chance of bad consequences, loss, etc.'.

RATIONAL DECISION MAKING UNDER UNCERTAINTY

It was Humpty Dumpty in Lewis Carroll's *Through the Looking Glass* who said 'When *I* use a word, it means just what I choose it to mean - neither more nor less'. As may be clear from the previous section, semantic difficulties tend to bedevil the discussion of risky decision making, so it is useful to indicate now just what meanings are chosen for some of the terms that are used in this paper.

*Paper presented at the 18th conference of the Agricultural Economic Society of South Africa in April 1981 at Bloemfontein. Prof. Hardaker is Associate Professor and Head, Department of Agricultural Economics and Business Management, University of New England, Armidale, N.S.W. 2351, Australia.

A *decision* involves a *choice* by a person (or a group of people) amongst a set of alternative *actions (*or *acts*). The *consequences* of the selected action depends on the *outcomes* of *uncertain events* or *uncertain quantities,* i.e. the consequences are uniquely defined for a particular action chosen by the decision maker and a given outcome of the uncertain event. Because the consequences are *risky,* each action open to the decision maker can be viewed as a *risky prospect.* The decision maker is assumed to hold *beliefs* about the occurrence of the uncertain events bearing on his decision as well as *preferences* for the possible consequences. A *rational decision* is defined as one that is consistent with the decision maker's beliefs and preferences.

The methods of *decision analysis,* to which the above terminology apply, are based on the assumption that decomposition of real decisions into their component parts, followed by analysis that integrates the components into a choice consistent with the elicited beliefs and preferences of the decision maker, is better than wholly intuitive choice, at least for some decisions. No doubt not everyone will accept this assumption. Certainly, decision analysis has its costs in time and effort and these costs are not justified for minor, every-day decisions.[2] It is a matter of judgment which decisions are important enough to warrant analysis. Similarly, judgment is needed to determine how much detail should be embodied (and how much cost is to be incurred) in any analysis that is to be performed. In this sense, decision analysis provides a satisficing rather than an optimising model of risky choice.

Relatedly, it is worth pointing out that, by the nature of uncertainty, decision analysis cannot guarantee correct choice. Where chance is involved it must be expected that some decisions will turn out well and others badly, even if all have been made in a considered fashion. When uncertainty prevails it is necessary to distinguish between 'good' decisions, that are consistent with the decision maker's beliefs and preferences, and 'right' decisions, that turn out to be correct in the light of the uncertain outcomes that eventuate. 'Right' decisions can never be identified for sure *ex ante* in risky choice and are only identifiable occasionally *ex post.* Seldom can one know what would have happened if some other action had been chosen. In any case, such information, if available, is only a matter of curiosity.

MEASURING BELIEFS

The decomposition of decision problems into separate assessments of beliefs and preferences requires first that some way be found of measuring the decision maker's beliefs. Subjective probabilities have been proposed for this purpose (Ramsey, 1926; De Finetti, 1937; Savage, 1954). The subjective probability that a person assigns to the outcome of an uncertain event may be said to measure his degree of belief in that outcome. Savage (1954) has formalised a theory of consistent behaviour under uncertainty according to which a person's ranking of alternative actions implicitly defines his subjective probabilities for relevant uncertain events.

An operational definition of subjective probability has been derived using the notion of a reference lottery (Anscombe and Auman, 1963). This is a (real or imaginary) lottery wherein the probability of winning a desirable prize depends on a known frequency or proportion. For example, the reference lottery may depend on a single random drawing of a red chip from a masked bag containing a known proportion of red and green chips. Then a person's subjective probability for an uncertain outcome E is the proportion of red chips that makes him just indifferent between the reference lottery that pays a desirable prize X if a red chip is drawn and zero otherwise, and another lottery that pays the same prize X if E is the outcome and zero if it is not.

The subjective nature of probabilities as statements of belief makes them essentially personal judgements. (Indeed, they are sometimes called personal probabilities, see, e.g., Savage, 1971.) This means that two individuals can reasonably assign different probabilities to the same uncertain outcome. Both are 'right' provided only that both individuals make their assessments consistent with their individual inner feelings of uncertainty. The personal nature of the measurement of beliefs as subjective probabilities emphasises the sovereignty of the decision maker in choices that affect his welfare. It is the decision maker who must bear the consequences - good or ill - of his decision and therefore his beliefs are relevant to the analysis of his choice.

While the subjective and personal nature of probabilities means that there are no 'right' or 'wrong' probabilities, there are two conditions that a rational individual would wish to impose on his probability judgments. First, as already noted, such probabilities should be consistent with the individual's true feelings of uncertainty. Thus, for example, the probability assigned to some event should be independent of the consequences arising from that event. A rational person will not let the possibility of good or bad consequences influence his assessment of the chances of those consequences occurring. Formally, probabilities assigned to outcomes and preferences for consequences should be independent.

Relatedly, there is a tendency to let the degree of 'objectivity' of a probability judgment affect the value assigned. An assessor may say 'I think there is about a 0,3 chance of outcome E occurring, but because I am not sure I will assign a probability of 0,2'. This too is not rational and such errors can usually be avoided by the reference lottery technique already described.

Attempts to keep probability assessors 'honest' have led to the development of scoring rules which have the property that the assessor can maximise his score only by providing probabilities consistent with his true beliefs. There are a number of rules that meet this requirement (e.g. Murphy and Winkler, 1970; Savage, 1971; Matheson and Winkler, 1976) but to date there appear to have been few cases when such rules have been routinely employed in practice.

A second condition on subjective probabilities is that they must conform with the laws of probability. For example, they must be restricted to numbers between 0 and 1,0 and should sum to 1,0 over the mutually exclusive and collectively exhaustive set of possible events.

A result that derives from the properties of probabilities is Bayes' theorem which, in the form of discrete probabilities, states that

$$P(O_i|z_k) = \frac{P(O_i)\,P(z_k|O_i)}{\Sigma_i P(O_i)P(z_k|O_i)}$$

where

$P(O_i|z_k)$ is the posterior probability of event O_i given that some particular forecast outcome, experimental result or sample value z_k has been observed;
$P(O_i)$ is the prior probability of the event O_i before z_k has been observed;
$P(z_k \mid O_i)$ is the conditional probability of observing z_k given that O_i is the actual outcome.

The importance of this noncontroversial theorem, which was originally proposed by an English clergyman, Rev. Thomas Bayes (1763), lies in the fact that it tells a probability assessor how he should revise his probability judgments in the light of new information. The degree of confidence the individual places in the new information is relected in the likelihood $P(z_k|O_i)$. In many applications this probability is determined by the nature of the sampling process giving rise to the observation z_k. Experience shows that, using a purely intuitive approach, many people fail to take full account of additional information and hold too strongly to their prior beliefs. This phenomenon is a form of *conservatism* (Tversky and Kahneman, 1974). A rational person will aim to eliminate conservatism by using Bayes' theorem to exploit the full value of new information.[3]

Generalising from the case of Bayes' theorem, a rational person will want to make his subjective probability judgments as objective as possible (or, strictly, since objective evidence usually has a cost, as objective as is worthwhile) and will seek to achieve consistency in his network of beliefs. Thus, if a person believes some set of data to be reliable and relevant to a particular uncertain event, he will assign subjective probabilities that reflect the relative frequencies embodied in those data.

A number of procedures have been developed and tried for assessing subjective probabilities (see, e.g. Spetzler and Stael von Holstein, 1975; Anderson, Dillon and Hardaker, 1977, Ch. 2). There is also a substantial literature, reviewed by Hogarth (1975), on the cognitive processes involved in the assessment of probabilities, while Lichtenstein, Fischhoff and Phillips (1977) have reviewed the state of the arts in the 'calibration' of probabilities. Calibration is concerned with measuring how well assessed probabilities conform with frequencies subsequently observed.

A disappointing feature of the work described above on the measurement of beliefs is that relatively few studies have been reported dealing with subjective probability assessments by farmers. Among the studies that have been done are those of O'Mara (1971), who elicited subjective probability distributions from a sample of farmers in Mexico for two maize technologies, and of Herath (1980) who obtained broadly the same sort of information from two groups of rice farmers in Sri Lanka. In interviews with 76 Californian peach growers, Carlson (1970) elicited subjective probability distributions of losses from crop disease outbreaks, while Roumasset (1976) combined Filipino farmers' subjective probabilities of specified disastrous outcomes with experimental data to derive subjective expected production functions for fertilizer application to rice. Mesquita and Dillon (1978) have reported on differences in subjective crop yield distributions between small land owners and sharecroppers in northeast Brazil. They found that averaged distributions obtained from the two groups were quite similar and were appreciably positively skewed. Lin, Dean and Moore (1974) combined Californian vegetable growers' subjective probability distributions for individual crop returns with correlation coefficients derived from historical data to construct a covariance matrix for use in a subjective risk programming analysis. Finally, in this short list of agricultural applications, Sharma (1979) obtained estimates of subjective distributions of both traditional and new varieties of wheat from a sample of Nepalese farmers. He sought to relate, on the one hand, adoption of new varieties to differences in subjective means and variances, and, on the other hand, he tried to relate these two moments of the elicited distributions to socio-economic characteristics of the farmers. His results were rather disappointing, emphasising how little is known about factors affecting farmers' cognitive processes in assessing uncertainty. Similarly, no studies have been found that calibrate probability assessments by farmers by relating these probabilities to empirically observed frequencies, although Francisco and Anderson (1972) have demonstrated the existence of conservatism in a sample of Australian pastoralists in revising subjective prior probabilities in the light of additional information.

The subjective or Bayesian view of probability has not been without its critics and a lively debate has been taking place over the years (see, e.g., Hartley vs. Schlaifer, 1963; Bross vs. Good, 1969; Hamaker, 1977 vs. Good, 1978 and Moore, 1978). The differences of opinion reflected in these contributions represent different concepts of probability itself. There are, broadly speaking, three schools of thought about the nature of probability

- the classical, the relative frequency and the subjective schools.

The classical view of probability developed during the sixteenth century in relation to games of chance. According to this view, probabilities can be determined *a priori*. Thus, if an uncertain event has n mutually exclusive, equally likely and collectively exhaustive outcomes, and if event E contains m of these outcomes, then the probability of E is m/n, i.e. $P(E) = m/n$ (Holloway, 1979, p. 78).

The practical limitations of this view of probability are obvious. Few uncertain events in real life have the properties that allow probabilities to be determined *a priori*. The assumption that events are equally likely, which in the classical view is based on the so-called 'principle of insufficient reason' (Laplace, 1814), is seldom plausible in practice. Even in relation to uncertain events such as the toss of a coin or the throw of a die, the notion of an ideal, perfectly balanced coin or die is not one that can exist in reality. These limitations are recognised in the second view of probability based on relative frequency.

The *relative frequency* view of probability is based on the use of sample data. The probability of an event is taken to be the number of occurrences divided by the sample size, at least for fairly large samples. (Strictly, the probability is the limit of the relative frequency as the sample size goes to infinity, but since an infinite sample size has no practical meaning, neither does this strict definition.)

The relative frequency definition of probability has intuitive appeal in some circumstances but not in others. For example, if (for want of something better to do) I threw a drawing pin into the air 1 000 times and observed that it came down point upwards on 423 occasions, it seems reasonable to say that the probability of this event (for the particular drawing pin) is approximately 0,423. But if I observed that, over the last 1 000 recorded sales, the price of farmland in a given region has been more than $500 per hectare on 423 occasions, it would be very naive of me to assign a probability of 0,423 to a price above $500 for the next sale. The reason, of course, is that it is not plausible to regard the previous price observations as independent, so that the relative frequency definition of probability cannot be applied. Moreover, the definition is inapplicable to many, probably most, uncertain events of importance in decision making. A definition of probability that excludes many of the cases of interest is obviously inadequate.

The subjective view of probability suffers from no such defects. All kinds of events are encompassed. *A priori* knowledge or relative frequency data can be incorporated as appropriate. The classical and relative frequency schools are sometimes grouped together as being based on the notion of 'objective' probability. The essential difference between objectivists and subjectivists is that objectivists view probabilities as characteristics of physical phenomena while subjectivists view them as the state of knowledge of a given individual.

Objectivists often argue that the use of subjective probabilities is 'unscientific'. Subjectivists reply that they do strive for as much 'scientific objectivity' as is attainable (or as is worthwhile) in assessing and using subjective probabilities (Good, 1976). They argue that complete objectivity is a myth in the sense that all forms of analysis involve human judgments. The statistician who believes in the relative frequency view must still decide which data to collect and how to interpret those data. For example, conventional tests of significance are no more than stereotyped value judgments (Dillon and Officer, 1971). Subjectivists argue that, if 'scientific' is taken to mean 'logical, rational and consistent', then by honestly recognising the role of judgment in analysis, they are being more scientific than objectivists (Holloway, 1979, p. 290). Finally, of course, most important decision problems would remain unresolved if analysis were to be confined to cases where abundant data exist.

MEASURING PREFERENCES

It is commonly observed that people do not base decisions under uncertainty on the expected value or mathematical expectation of the risky consequences of alternative actions. For example, when given a choice between

(a) winning $1 000 for sure, or

(b) winning $5 000 with a probability of 0,25,

most people opt for (a) even though it has a lower expected value than (b). The first recorded solution to this puzzle was that of Daniel Bernoulli (1738) who argued that individuals made risky choices on the basis of what he called 'moral expectations' and is today called 'expected utility'. Bernoulli proposed the existence of a non-linear utility function which can be used to encode an individual's preferences for money consequences[4] such that risky choice would be properly based on (subjective) expected utility. Bernoulli had the misfortune to advance this idea some 200 years ahead of its time and the idea was rediscovered, apparently independently by Ramsey in 1926 and again independently by Von Neumann and Morgenstern in 1947.

The notion of a *certainty equivalent* is central to the measurement of preferences. The certainty equivalent (CE) of a risky prospect is that sure value, in terms of the measure of consequences being used, which the decision maker is just willing to accept in lieu of the risky prospect. The relationship between the CE and the expected value (EV) of the consequences tells us something about the decision maker's attitude to risk. If the person is averse to risk, he will assign a CE less than the EV. This is the normal case. However, some people have a preference for risk, and for them CE > EV, while others are indifferent to risk and have CE = EV. We can illustrate these three cases with an example. Given the risky prospect of winning $1 000 with a probability of 0,5, a risk averse person will assign a CE of less than $500, a risk preferrer will require more than $500 before he will 'trade' the risky prospect, while someone indifferent to risk will accept exactly $500.

These three cases can also be distinguished in terms of the shape of utility functions, as illustrated in Figure 1. In case (a), with risk aversion, there is diminishing marginal utility of money ($d^2U/dx^2 < 0$). With risk preference (case (b)), the marginal utility of money increases ($d^2U/dx^2 > 0$), while in case (c), with indifference to risk, the marginal utility of money is constant ($d^2U/dx^2 = 0$).

Methods of eliciting utility functions involve asking subjects to specify their CEs for specified risky prospects or else require them to specify pairs of risky prospects between which they are indifferent. These elicitation methods, described in Anderson, Dillon and Hardaker (1977, Ch.4), have been used in a number of studies to elicit farmers' utility functions (see, e.g., Officer and Halter, 1968; O'Mara, 1971; Francisco and Anderson, 1972; Lin, Dean and Moore, 1974; Webster, 1977). Other studies with farmers have been directed at quantifying farmers' risk attitudes, rather than at eliciting their complete utility functions. In these cases, exact indifference points are not sought, but subjects are asked to choose between alternative risky prospects (see, e.g., Dillon and Scandizzo, 1978; Binswanger, 1980; Bond and Wonder, 1980).

Of these studies, the work of Binswanger is particularly important. He studied risk attitudes of Indian peasant farmers and was able to use real money prizes for some of the preference elicitation experiments that he conducted. His results showed that, at non-trivial levels of payoffs, virtually all respondents were moderately risk averse with little variation according to personal characteristics.[5] This finding is somewhat at variance with the other studies noted above which, although indicating that most farmers are risk averse, showed a wide dispersion of risk attitudes, including evidence that some farmers have a preference for risk. The validity of these results is brought into question by Binswanger's general findings and by the evidence he uncovered of both non-replicability of results over time and investigator bias when hypothetical pay-offs were used. The introduction of real money pay-offs produced a reduction in the spread of degrees of risk aversion in the sample of respondents. There also appeared to be an improvement in the introspective capacity of subjects with experience of the elicitation method so that, later in the series of experiments, they were able to give more consistent responses. Binswanger's results emphasise the need for care in the design, conduct and interpretation of studies intended to measure farmers' preferences. In particular, there may be a need to include a 'training' component in such studies to familiarise subjects with the concepts involved and to enable them to improve their introspective abilities.

Another approach to assessing farmers' responses to risk involves econometric analysis of cross-section or time-series data. For example, Moscardi and De Janvry (1977) used cross-section data from individual farms to make comparisons of factor marginal products calculated for the expected profit-maximising point with marginal products for the actual levels of factor use. Their analysis, using data relating to fertiliser use by farmers in the Puebla Project area in Mexico, generated a residual measure of risk aversion. A similar study, but not involving quantification of the risk aversion measure, was carried out in Kenya by Wolgin (1975). Work on supply behaviour of farmers, incorporating consideration of their responses to changes in risk, by Behrman (1968), Just (1974) and Anderson et al. (1980), amongst others, has generally confirmed the existence of widespread risk aversion, even though these studies have not measured unambiguously the overall degree of risk aversion present.

All the above discussion of measurement of farmers' preferences refers to cases where these preferences were assumed to relate to a single monetary measure of consequences, usually income. However, utility theory extends to cases where

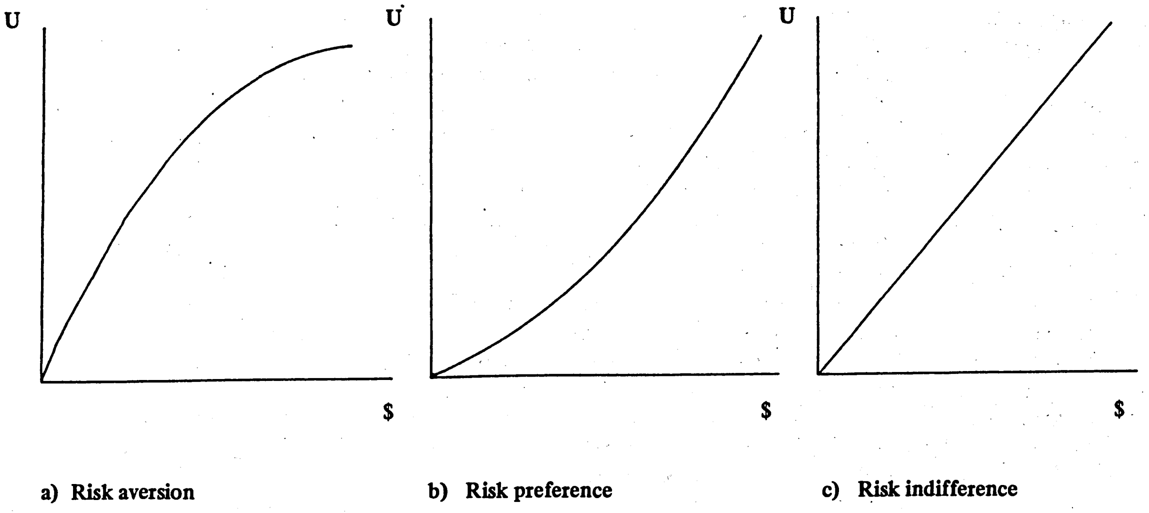

Figure 1. Risk attitudes and the shape of utility functions

consequences are measured in more than one dimension and where trade-offs may exist between one dimension of consequences and another. Thus, for example, most farmers, like most other people, may be willing to trade off income for leisure, at least to some extent. Keeny and Raiffa (1976) have provided a comprehensive treatment of multi-attribute preference theory and its application to decisions under uncertainty, while Herath (1980) has reported one of the few agricultural applications. There are probably too many unresolved issues in the application of single attribute preferences theory to agriculture to expect any spate of multi-attribute studies of agricultural decision making in the near future.

INTEGRATING BELIEFS AND PREFERENCES IN THE ANALYSIS OF DECISIONS

The way in which beliefs and preferences are integrated to prescribe an optimal decision is by appeal to the subjective expected utility (SEU) theorem, also known as Bernoulli's principle. This superficially simple but extraordinarily powerful theorem states that the utility of a risky prospect is found as the (subjective) probability-weighted average of the utilities of the possible consequences. Then the optimal action in any decision under uncertainty is that yielding the highest (expected) utility.

The axioms or assumptions upon which the SEU theorem rests are relatively undemanding in the sense that most people agree that at least they would wish to behave in a manner consistent with those axioms when taking important decisions, even though in practice they may not always achieve that degree of rationality. A number of slightly different formal proofs of the theorem have been provided (e.g. von Neumann and Morgenstern, 1947; Luce and Raiffa, 1957; Arrow and Hurwicz, 1972; Radner, 1972). However, the following statement of the basic axioms, provided by Dillon (1979), is sufficient to give their flavour. In this treatment, he denotes the decision maker's subjective probability distribution for the risky consequences if he chooses the j-th action.

Ordering. A person either prefers one of two probability distributions, denoted by h_1 and h_2, of consequences, or he is indifferent between them. If there are three distributions and he prefers h_1 to h_2 and h_2 to h_3, then he prefers h_1 to h_3.

Continuity. If a person prefers probability distribution h_1 to h_2 and h_2 to h_3, then there exists a unique probability p such that he is indifferent between h_2 and a lottery with a probability p of yielding the distribution h1 and a probability (1 - p) of yielding the distribution h_3.

Independence. If a person prefers h_1 to h_3 and h_3 is some other probability distribution, then he will prefer a lottery with h_1 and h_3 as prizes to a lottery with h_2 and h_3 as prizes if the probability of $h_1$and h_2 occurring is the same in both lotteries.

For a person whose behaviour is consistent with these axioms there exists a utility function U with the properties that consequence A is preferred to consequence B if and only if $U(A) > U(B)$ and the utility of an action with risky consequences can be found as the probability-weighted average of the utilities of the consequences.

The important point about the SEU theorem is that all dimensions of preference are captured simply by calculating the expected value of utility. In particular, the effect of risk and risk aversion (or preference) is fully accounted for by this measure and it is not necessary to consider higher moments, such as the variance of utility.

A variety of methods have been developed to put the SEU theorem to use in the analysis of risky decision problems. These methods range from relatively simple tabular or diagrammatic approaches to the incorporation of an SEU objective function into complex operations research or systems simulation models. The appropriate degree of complexity of a given analytical model depends, of course, on the nature of the decision problem being studied and on the resources available for its analysis. However, a review of the methods of decision analysis is beyond the scope of this paper. Such a review, including some agricultural applications, is provided by Anderson, Dillon and Hardaker (1977, Chs 4-8).

SOME IMPLICATIONS OF THE DECISIONS ANALYSIS APPROACH

Normative Applications to Farm-Level Choice

The theory of risky choice outlined above is essentially normative or prescriptive in nature. It concerns the question of how an individual should act when confronted with a range of risky alternatives. In practice, decision analyses always involve simplifications of reality. It is seldom possible to detail all the available actions and all the possible consequences. A decision made today may have implications extending far into the future. Practical considerations usually dictate that some planning horizon or cut-off date must be adopted such that differences in consequences beyond that date are ignored. All such simplifications mean, of course, that the results of the decision analysis can be no more than a guide to choice for the decision maker.

Decision analysis is essentially 'artistic' in nature and if, through lack of time or other resources, or through bad judgment, the analysts' representation of the decision problem is poor, it is reasonable for the decision maker to reject the conclusions reached. On the other hand, if there is proper involvement of the decision maker in the process of model construction and analysis, especially if the analyst and the decision maker are the same person, the decision maker should be prepared to act on the basis of the conclusions reached.

Little research seems to have been done on the extent to which various types of decision makers find decision analysis useful. There are some reports in the literature that business men find the approach helpful (Swalm, 1966; Brown, 1970) and the method appears to have passed the market test in that it is used, apparently successfully, by some commercial management consultants. However, very few studies have been done to assess farmers' reactions. (A rare exception is Jackson, 1974). With greater popularisation of the method, evaluations of the approach might be expected to appear before too long.

Multiperson Decision Situations

In addition to its normative orientation, the model of risky choice outlined here relates primarily to a situation where there is one decision maker whose beliefs and preferences are to used in the analysis and who bears the consequences of his choice. This is seldom the case in practice. Usually more than one person is involved in any decision, even if only in the sense of being affected by the consequences. Certainly this is often the case in farming where members of the farm family, farm workers, or perhaps consumers of farm output, may all be affected by a farm management decision. Unfortunately, the extension of the methods of decision analysis to multiperson decision problems is generally not a simple matter.

Several different multiperson decision situations can be distinguished (MacCrimmon, 1973). Three of particular importance in agriculture are: (a) group choice situations, wherein a number of people are collectively responsible for a decision; (b) situations with many individual and independent decision makers; and (c) social choice situations, where the power of decision rests with government or one of its agencies, but where many people are affected by the decision consequences.

Examples of group choice situations are decisions made by a family or by a board of directors. At first sight it might seem that the decision analysis approach should extend directly to such situations in that a rational group would seek first to form a consensus of beliefs and preferences and then to act in a way consistent with the consensus. Unfortunately, unless there is complete unanimity within the group, or unless one member acts as a dictator, it can be shown that there is no way of amalgamating beliefs and preferences of group members to achieve consistent and rational group choice (Zeckhauser, quoted by Raiffa, 1968, p. 230; see also Arrow, 1967).

Of course, it is common experience that some groups do function as effective decision units, blithely unaware of the theoretical difficulties. On the other hand, it is not unusual for committees of one kind or another to attract criticism for inconsistency in decision making.

One solution to the difficulties of group choice is for the group to allow an individual to act on its behalf. This may be more or less what happens in many farm families. If the group is reasonably coherent, in the sense that there are good relations between members, the accepted decision maker is likely to try to account for what he knows are the beliefs and preferences of the other members of the group. By this means, the views of the group members can be reasonably well integrated in a manner consistent with the precepts of individual rational choice.

Problems involving many individual decision makers arise in agriculture, for example in relation to attempts by agricultural researchers to design new technologies that will appeal to many farmers. Similar problems arise in agricultural policy making, for instance in the design of a price stabilisation scheme for some farm commodity, and in agricultural extension in deciding what farming practices should be promoted to some target group of farmers. These sorts of questions can only be rigorously tackled by recognising the effects of risk and farmers' attitudes to it. The difficulty is that farmers vary in their attitudes to risk, so that the concept of one universally optimal choice is not valid.

Some segregation of alternative risky prospects can be achieved without detailed knowledge of the utility functions of the target population using the method of stochastic efficiency analysis (Anderson, 1974; Anderson, Dillon and Hardaker, 1977, Ch. 9). By assuming, for example, that farmers generally prefer more income to less and that most of them are averse to risk, it is possible to partition a set of risky prospects, such as alternative farming technologies, into those that are risk efficient and those that are not. It can be shown that the optimal technology for an individual farmer whose preferences are in conformity with the assumptions will be found in the efficient subset. The disadvantage of stochastic efficiency analysis, however, is that the efficient subset might be quite large and can be reduced in number only by having more intimate knowledge of the preferences of the farmers in the target group. Thus, Meyer (1977) has shown how the size of the efficient set can be further reduced by establishing only a lower and an upper bound on the measure of decision makers' risk aversion. Drynan (1977) has developed procedures to apply this approach to the evaluation of agricultural experiments.

If the farmers' utility functions cannot be elicited, and nothing is known about their degree of risk aversion, it can be argued that it would be legitimate to use the 'everyman's' utility function $U = \ln X$, originally proposed by Bernoulli (1738). While such an approach is obviously very arbitrary, it is no more so than the implicit assumption of linear utility that is made when risk is ignored.

Social decision problems in agriculture relate to such questions as whether the government should introduce a compulsory program for the control of some disease of farm animals, or whether it should intervene in the market for some farm product to try to support the price. Decisions of this kind are important in that they are likely to affect the welfare of large numbers of people, including both farmers and consumers. Moreover, such decisions often have highly risky consequences. They therefore seem to be good candidates for decision analysis in that the costs of analysis should be readily recouped from the benefits to be expected from better choices. However, the application of decision analysis to social choice confronts some important difficulties. For example, whose beliefs and preferences are to be used?

In social choice situations it often seems appropriate to obtain subjective probability judgments from experts. Commonly a number of experts are consulted and considerable progress has been made in developing methods for forming a consensus of opinion in such a situation (e.g. Dalkey, 1967; Winkler, 1968; Pill, 1971; Hogarth, 1975). On the other hand, the identification of an appropriate social utility function remains a much more contentious issue (Arrow, 1967; Fishburn, 1973; Keeney and Kirkwood, 1975; Mueller, 1976). Despite the theoretical difficulties, a number of examples of use of decision analysis for social choice have been reported (Ellis and Keeney, 1972; Howard, Matheson and North, 1972; Keeney, 1973; Keeney and Nair, 1975). Once again, agricultural examples are scarce.

The use of decision analysis for decision problems under uncertainty in the public domain provides a means of making explicit the judgmental components of such choices. It therefore should permit the clearer identification of the nature of differences between groups or individuals urging different decisions. For example, a dispute between conservationists and developers might be usefully disaggregated into differences in beliefs about the likely consequences of development (e.g., what species will be threatened and how seriously), and differences in preferences for natural environments versus developed environments. Better information should narrow differences in beliefs, but differences in preferences are basically irreconcilable.

It can be argued that dissecting and exposing differences between contending viewpoints should be conducive to more rational social choice. Of course, politicians may prefer to make social choices without exposing their prejudices more than is absolutely necessary, but that is no reason for economists to follow suit.

Positive Applications

As emphasised several times already, decision analysis based on the SEU theorem has been developed mainly as a normative or prescriptive theory of choice. Nevertheless, the plausibility of the axioms has led some workers to suggest or investigate the possibility of using the SEU model as a positive or descriptive theory of choice. Direct tests of the predictive power of the SEU model for farmers' behaviour have given rather mixed but not too unfavourable results (e.g., Officer and Halter, 1968; O'Mara, 1971; Lin, Dean and Moore, 1974; Herath, 1980).

A good normative model of risky choice by farmers would obviously be useful for predicting the response to alternative agricultural policy decisions. The evidence seems to be clear that farmers, on the whole, are risk averse and do respond to changes in risk levels. It seems reasonable, therefore, that the research findings do suggest that an SEU model predicts farmers' behaviour better than one that ignores risk. Of course, the question is not whether farmers actually go through the process of dissecting their risky decisions into separate assessments of beliefs and preferences, but rather whether they tend to behave as if they have done so.

There are at least two difficulties in the way of use of the SEU model as a behavioural theory of choice. First, there is abundant evidence in the phychological literature that people do not always behave in a manner consistent with the axioms of rational choice (Edwards, 1961; Hogarth, 1975; Slovic, Fischhoff and Lichtenstein, 1977). Indeed, if they did, prescriptive decision analysis would have no value. The psychological literature suggests that the SEU model will predict behaviour very imperfectly, especially for difficult decisions. The empirical evidence from agriculture seems to confirm that such a gap between predictions and farmers' behaviour does indeed exist.

The second difficulty is that other models of behaviour under risk seem to be just about as good as the SEU model. As Dillon (1979, p. 36) notes, 'to distinguish between the various proposed positive theories of expected utility, expected profit, safety first, focus-loss and games-against-nature types will require far more robust tests or test situtions than have currently been studied'. Until such tests are developed, or until we know more about farmers' cognitive processes, the case for use of the SEU model for positive analyses seems to rest more on faith than on firm empirical foundations.

CONCLUDING COMMENT

Risk and uncertainty are undoubtedly important in agriculture and therefore it is also important that agricultural economists have both a good theory of risky choice and effective methods of analysing risky decisions. The SEU theorem and decision analysis together meet these requirements well. Of course, not all real decision situations are amenable to systematic study using decision analysis, and some thorny theoretical issues remain unresolved. But at least a good start has been made and the rate of growth of the literature in the field seems to indicate that further advances can be expected.

The analysis of risky decisions is not easy and it is reasonable to question the feasibility of the analytical methods that have been developed. It must be admitted that detailed analysis will often not be justified. As noted above, there are occasions when the beliefs and preferences of relevant decision makers cannot be elicited or when the costs of analysis are judged to exceed the expected benefits. Even in such cases, decision analysis provides a framework for thinking about the decision to be made and about the impact of risk on choice. No longer can risk be swept aside as irrelevant in agricultural decision making. If practical considerations dictate that something less than the full decision analysis approach must be adopted, then at least the required simplifications can be made with a full appreciation of their implications. Fortunately, however, the expanding range of methods at the decision analyst's command, coupled with improving access to computers in agriculture to handle the tedious calculations, will enlarge the range of problems that can be studied.

REFERENCES

ANDERSON, J.R. (1974), 'Risk efficiency in the interpretation of agricultural production research', *Review of Marketing and Agricultural Economics* 42(3), 131-84.

ANDERSON, J., BLITZER, C., CANCHORS, T. and GRILLI, E. (1980). *A Dynamic Simulation Model of the World Jute Economy,* World Bank Staff Working Paper No. 391 (Revised), Washington, D.C.

ANDERSON, J.R., DILLON, J.L. and HARDAKER J.B. (1977). *Agricultural Decision Analysis,* Iowa State University Press, Ames.

ANSCOMBE, F.J. and Auman, R.J. (1963). 'A definition of subjective probability', *Annals of Mathematical Statistics* 34(1), 199-205.

ARROW, K.J. (1967). 'Values and collective decision making', in P. Laslett and W.C. Lunciman (eds), *Philosophy, Politics and Society,* 3rd series, Blackwell, Oxford, 215-32.

ARROW, K.J. and HURWICZ, L., (1972). 'An optimality criterion for decision-making under ignorance', in C.F. Carter and J.L. Ford (eds), *Uncertainty and Expectations in Economics: Essays in Honour of G.L.S. Schackle,* Blackwell, Oxford, 1-11.

BAYES, T. (1763). 'An essay towards solving a problem in the doctrine of chance', *Philosophical Transactions of the Royal Society* 53, 370-418, reproduced with a biography of Bayes in G.A. Barnard (1958), 'Studies in the history of probability and statistics: IX', *Biometrika* 45(3 and 4), 293-315.

BERHMAN, J.R. (1968). *Supply Response in Underdeveloped Agriculture,* North-Holland, Amsterdam.

BERNOULLI, D. (1738). 'Specimen theoriae novae de mensura sortis', St. Petersburg, translated by L. Somer (1954) as 'Exposition of a new theory of the measurement of risk', *Econometrica* 22(1), 23-36.

BINSWANGER, H.P. (1980). 'Attitudes towards risk: experimental measurement in rural India', *American Journal of Agricultural Economics* 62(3), 395-407.

BOND, G. and WONDER, B. (1980). 'Risk attitudes amongst Australian farmers', *Australian Journal of Agricultural Economics* 24(1), 16-34.

BORCH, K. (1968). 'Introduction', in K. BORCH and J. MOSSIN (eds), *Risk and Uncertainty,* McMillan, London, xiii-xv.

BROSS, I.D.J. (1969). 'Applications of probability: science vs pseudoscience', *Journal of the American Statistical Association* 64 (325), 51-7.

BROWN, R.V. (1970). 'Do managers find decision theory useful?', *Harvard Business Review* 48(1), 78-89.

CARLSON, G.A. (1970). 'A decision theoretic approach to crop disease prediction and control'. *American Journal of Agricultural Economics* 52(2), 216-23.

DALKEY, N.C. (1967). *Delphi,* P-3704, The Rand Corporation, Santa Monica, California.

DILLON, J.L. (1971). 'An expository review of Bernoullian decision theory', *Review of Marketing and Agricultural Economics* 39(1), 3-80.

DILLON, J.L. (1979). 'Bernoullian decision theory: outline and problems', in J.A. Roumasset, J-M. Boussard and I. Singh (eds), *Risk, Uncertainty and Agricultural Development,* SEARCA, Laguna, Philippines and A/D/C, New York.

DILLON, J.L. and OFFICER, R.R. (1971). 'Economic and statistical significance in agricultural research and extension: a pro-Bayesian view', *Farm Economist* 12(1), 31-45.

DILLON, J.L. and SCANDIZZO, P.L. (1978). 'Risk attitudes of subsistence farmers in northeast Brazil: a sampling approach', *American Journal of Agricultural Economics* 60(3), 425-35.

DRYNAN, R.G. (1977). Experimentation - its value to the farm decision maker, Ph.D. thesis, University of New England, Armidale, N.S.W.

EDWARDS, W. (1961). 'Behavioral decision theory', *Annual Review of Psychology* 12, 473-98.

ELLIS, R.M. and KEENEY, R.L. (1972). 'A rational approach for government decisions concerning air pollution', in A.W. Drake et al. (eds), *Analysis of Public Systems,* MIT Press, Cambridge, Mass.

DE FINETTI, B. (1937). 'La prévision: ses lois logique, ses sources subjectives', *Annales de l'Institut Henri Poincaré (Paris)* 7, 1-68, English translation by H.E. Kyburg (1964), 'Foresight: its logical laws, its subjective sources', in H.E. Kyburg and H.E. Smokler (eds), *Studies in Subjective Probability,* Wiley, New York, 93-158.

FISHBURN, P.C. (1973). *Theory of Social Choice,* Princeton University Press.

FRANCISCO, E.M. and ANDERSON, J.R. (1972). 'Chance and choice west of the Darling', *Australian Journal of Agricultural Economics* 16(2), 82-93.

GOOD, I.J. (1969). 'Applications of probability: science vs. pseudoscience - reply', *Journal of the American Statistical Association* 64(325), 61-6.

GOOD, I.J. (1976). 'The Bayesian influence, or how to sweep subjectivism under the carpet', in W.L. Harper and C.A. Hooker (eds), *Foundations of Probability Theory, Statistical Influence and Statistical Theories of Science,* Vol. 2, Reidel, Dordrecht, 119-68.

GOOD, I.J. (1978). 'Alleged objectivity: a threat to the human spirit?', *International Statistical Review* 46(1), 65-6.

HAMAKER, H.C. (1977). 'Bayesianism: a threat to the statistical profession?', *International Statistical Review* 45(2), 111-5.

HARTLEY, H.O. (1963). 'In Dr. Bayes' consulting room', *American Statistician* 17(1), 22-4, and 'Reply', 17(4), 37.

HERATH, H.M.G. (1980). Resource allocation by rice farmers in Sri Lanka: a decision theoretic approach, Ph.D. thesis, University of New England, Armidale, N.S.W.

HOGARTH, R.M. (1975). 'Cognitive processes and the assessment of subjective probability distributions', *Journal of the American Statistical Association* 70(350), 271-91.

HOLLOWAY, C.A. (1979. *Decision Making under Uncertainty: Models and Choices.* Prentice-Hall, Englewood Cliffs.

HOWARD, R.A., MATHESON, J.E. and NORTH, D.W. (1972). 'The decision to seed hurricanes', *Science* 176(4040), 1191-202.

JACKSON, R. (1974). Utility analysis: futile or fertile, M.Ec. thesis, University of New England, Armidale, N.S.W.

JUST, R.E. (1974). *Econometric Analysis of Production Decisions with Government Intervention: The Case of California Field Crops.* Giannini Foundation Monograph No. 30, Berkeley, California.

KEENEY, R.L. (1973). 'A decision analysis with multiple objectives: the Mexico City Airport', *Bell Journal of Economics and Management* 4(1), 101-17.

KEENEY, R.L. and KIRKWOOD, C.W. (1975). 'Group decision making using cardinal social welfare functions', *Management Science* 22(4), 430-7.

KEENEY, R.L. and NAIR, K. (1975). 'Decision analysis for the siting of nuclear power plants - the relevance of multiattribute utility theory', *Proceedings of the IEEE* 63(3), 494-501.

KEENEY, R.L. and RAIFFA, H. (1976). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs,* Wiley, New York.
KNIGHT, F.H. (1921). *Risk, Uncertainty and Profit,* Houghton Mifflin, Boston.
LAPLACE, P.S. (1914). *Essai Philosophique sur les Probabilitês,* translated by F.W. Truscott and F.I. Emory (1951) as *A Philosophical Essay on Probabilities,* Dover, New York.
LICHTENSTEIN, S., FISCHHOFF, B. and PHILLIPS, L.D. (1977). 'Calibration of probabilities: the state of the art', in H. Jungermann and G. de Zeeuw (eds), *Decision Making and Change in Human Affairs: Proceedings of the Fifth Research Conference on Subjective Probability, Utility, and Decision Making, Darmstadt, 1975,* Reidel, Dordrecht, 275-324.
LIN, W., DEAN, G.W. and MOORE, C.V. (1974). 'An empirical test of utility vs. profit maximisation in agricultural production', *American Journal of Agricultural Economics* 56(3), 497-508.
LUCE, R.D. and RAIFFA, H. (1957). *Games and Decisions: Introduction and Critical Survey,* Wiley, New York.
MacCRIMMON, K.R. (1973). Theories of collective decision, Invited review paper for Fourth Research Conference on Subjective Probability, Utility and Decision Making, Rome, University of British Columbia, Vancouver.
MATHESON, J.E. and WINKLER, R.L. (1976). 'Scoring rules for continuous probability distributions', *Management Science* 22(10), 1087-96.
MESQUITA, T.C. and DILLON, J.L. (1978). 'Alguns aspectos das atitudes dos pequenos agricultores do Sertao do Ceará diante do risco', *Revista de Economia Rural* 16(2), 7-21.
MEYER, J. (1977). 'Second degree stochastic dominance with respect to a function', *International Economic Review* 18(2), 477-87.
MOORE, P.G. (1978). 'The mythical threat of Bayesianism', *International Statistical Review* 46(1) 67-73.
MOSCARDI, E. and DE JANVRY, A. (1977). 'Attitudes towards risk among peasants: an econometric approach', *American Journal of Agricultural Economics* 59(4), 710-6.
MUELLER, D.C. (1976). 'Public choice: a survey', *Journal of Economic Literature* 14(2), 395-433.
MURPHY, A.H. and WINKLER, R.L. (1970). 'Scoring rules in probability assessment and evaluation', *Acta Psychologica* 34(2/3), 273-86.
VON NEUMANN, J. and MORGENSTERN, O. (1947). *Theory of Games and Economic Behaviour,* 2nd edn, Princeton University Press.
OFFICER, R.R. and HALTER, A.N. (1968). 'Utility analysis in a practical setting', *American Journal of Agricultural Economics* 50(2), 257-77.
O'MARA, G.T. (1971). A decision-theoretic view of the microeconomics of technique diffusion in a developing country, Ph.D. thesis, Stanford University.
PILL, V. (1971). 'The Delphi method: substance, content, a critique and an annotated bibliography', *Socio-Economic Planning Sciences* 5(1), 57-71.
RADNER, R. (1972). 'Normative theory of individual decision: an introduction', in C.B. McGuire and R. Radner (eds), *Decision and Organization,* North-Holland, Amsterdam, 1-18.
RAIFFA, H. (1968). *Decision Analysis: Introductory Lectures on Choices under Uncertainty,* Addison-Wesley, Reading, Mass.
RAMSEY, F.P. (1926). 'Truth and probability', reprinted H.E. Kyburg and H.E. Smokler (eds)(1964), *Studies in Subjective Probability,* Wiley, New York, 61-92.
ROUMASSET, J.A. (1976). *Rice and Risk,* North-Holland, Amsterdam.
SAVAGE, L.J. (1954). *Foundations of Statistics,* Wiley, New York.
SAVAGE, L.J. (1971). 'Elicitation of personal probabilities and expectations', *Journal of the American Statistical Association* 66(336), 783-801.
SCHLAIFER, R. (1963). 'In Dr. Bayes' consulting room: comment', *American Statistician* 17(2), 36.
SHARMA, R.P. (1979). Uncertainty and subjective degrees of belief in the adoption of modern farming techniques: a case study of Nepalese farmers, M.Ec. dissertation, University of New England, Armidale, N.S.W.
SLOVIC, P., FISCHHOFF, B. and LICHTENSTEIN, S. (1977). 'Behavioral decision theory', *Annual Review of Psychology* 28, 1-39.
SPETZLER, C.S. and STAEL VON HOLSTEIN, C.A.S. (1975). 'Probability encoding in decision analysis', *Management Science* 22(3), 340-58.
SWALM, R.O. (1966). 'Utility theory: insights into risk taking', Harvard Business Review 44(6), 123-6.
TVERSKY, A. and KAHNMAN, D. (1974). 'Judgement under uncertainty: heuristics and biases', *Science* 185(4157), 1124-31.
WATSON, S.R. and BROWN, R.V. (1978). 'The valuation of decision analysis', *Journal of the Royal Statistical Society,* Series A, 141(1), 69-78.
WEBSTER, J.P.G. (1977). 'The analysis of risky farm management decisions: advising farmers about the use of pesticides', *Journal of Agricultural Economics* 28(3), 243-60.
WINKLER, R.L. (1968). 'The consensus of subjective probability distributions', *Management Science* 15(2), B61-75.
WOLGIN, J.M. (1975). 'Resource allocation and risk: a case study of smallholder agriculture in Kenya', *American Journal of Agricultural Economics* 57(4), 622-30.

FOOTNOTES

In writing this paper, I have drawn heavily on the work and advice of my colleagues, Jock Anderson and John Dillon, at the University of New England (UNE). For more complete treatments, in the UNE style, of many of the topics touched on in the paper, see especially Dillon (1971) and Anderson, Dillon and Hardaker (1977)

[1]'It was Frank H. Knight who first used "risk" and "uncertainty" as two different, well-defined concepts. His book *Risk, Uncertainty and Profit,* which appeared in 1921, opened the way for systematic studies of the uncertainty elements in economics, and Knight's terminology has been widely accepted by a whole generation of economists. It seems, however, that it no longer serves any useful purpose to distinguish between risk and uncertainty.' Borch (1968, p. xiii).

[2]For a formal treatment of the question of when decision analysis is worthwhile, see Watson and Brown (1978)

[3]As Good (1976) points out, there is no special reason why Bayes' theorem should always be applied starting with prior probabilities and proceeding to posterior probabilities. All that is required is consistency in all the probabilities. In some cases it may be sensible to start with the posterior probabilities and use the likelihoods to derive the priors. In other cases it may be useful to deduce the implied likelihoods

[4]The theory is valid for any measure of consequences, monetary or not. However, many economic decision problems can best be analysed using a monetary measure of consequence, which is therefore assumed here.

[5]Similar results have been obtained in further applications of Binswanger's experimental approach to small farmers in the Philippines and in El Salvador (T. Walker, personal communication, 1981)