3. Modelling Farm Decision Making under Uncertainty

'Nothing is certain but death and taxes'

- Anon.

3.1 Introduction

Agricultural production takes place in a dynamic and unpredictable environment and consequently farmers are constantly grappling with the uncertainty in the consequences of the decisions they make. As observed by Anderson and Hazell (1994), production risks which pervade agricultural systems can have wide-ranging economic, social and environmental costs. The sometimes significant variation in farm incomes from one year to the next provides an indication of the uncertainty under which farmers operate. The main causes of such variation are the natural, economic and biological elements over which the producer has little control, as well as imperfect knowledge of many aspects of the farming environment, such as new production technologies. This is all aptly recognised by Boisvert and McCarl (1990, p.1) when they state, inter alia, that:

> The biological nature of crop and livestock production, interacting with variable weather and environmental conditions, and changing demand, as well as unpredictable government policies, affects agricultural prices and can lead to wide year-to-year and seasonal swings in agricultural incomes and the well being of farm decision makers. The severity of these 'risk' responses varies from farming situation to situation, as do decision makers' responses. Unless these 'risk' responses are adequately reflected in planning models, the results generated in empirical analysis may bear little resemblance to actual decisions and may be of little use either in direct decision making or in policy analysis.

Decision analysis is a method that allows systematic and logical accounting for risk and uncertainty. It offers procedures by which decision makers can make reasoned, rational choices consistent with their perceptions of the level of uncertainty involved in a given decision problem, together with their attitude towards risk taking (Anderson et al. 1977). Various studies, including those by Smith and Capstick (1976), Harper and Eastman (1980), Patrick and Blake (1981), and Chibnik (1990), have shown that farmers are generally risk averse and consequently consider risk to be important in making business decisions.

This chapter deals with the application of decision analysis to agricultural production systems. An exhaustive discourse of decision making under risk and uncertainty is beyond the scope of this work and is left to such specialised texts as Anderson et al. (1977), Keeney and Raiffa (1976), Holloway (1979), Kleindorfer, Kunreuther and Schoemaker (1993). The discussion here will be limited to a few selected references relevant to the various methods broached. In Section 3.2, the general issues pertaining to the assessment and adoption of technology under risk and uncertainty in agricultural production are briefly examined only in as far as they relate to the questions at issue in this work. Some of the theoretical foundations of risky decision analysis are reviewed in Section 3.3. The focus of the discussion is the conceptual background of decision analysis based on a characterisation of risk and uncertainty in a Bayesian context. Various decision criteria and forms of efficiency analysis as applied in decision making under uncertainty are discussed in Section 3.4. The application of these decision criteria in mathematical programming techniques, particularly the expected utility maxim adopted in this work, is examined in Section 3.5. A few summary remarks are made in Section 3.6.

3.2 Technology assessment under uncertainty

A production technique may be defined as the process by which inputs are converted to outputs. A new technique of production is an input-output conversion process not previously applied by the producer (Anderson and Hardaker 1979). Such new production methods may include such options as improved crops, land and management practices as well as the adoption of new crop and livestock varieties such as Linola. The adoption process associated with a new production technique may be considered a relatively riskier prospect than existing production techniques due to the lack of information. Adesina and Baidu-Forson (1995) have observed that, by exposing farmers to 'new information', extension visits and farmer participation in workshops significantly influence adoption decisions.

A given innovation generally embodies several important characteristics that may influence individual adoption decisions. According to Anderson (1996), a major consideration in the significance or otherwise of a new risk should be its statistical relationship to the background risk. Adesina and Baidu-Forson (1995) have posited that the choice to adopt a particular agricultural technology is the end result of a complex set of inter-technology preference comparisons made by agricultural producers.

The attitudes of farmers towards risk, as well as their perception of risk, are significant in the choices they make between alternative production technologies. According to Lin and Milon (1993), consumers usually have subjective preferences for characteristics of products and their perceptions of the attributes of a product significantly influence their demand for it. Farmers as consumers of new technologies should thus be expected to have their adoption decisions influenced by their subjective perceptions. Kivlin and Fliegel (1967), Nowak (1992), Adesina and Zinnah (1993), Smith and Mandac (1995) and Adesina and Baidu-Forson (1995) have variously concluded that farmers' subjective assessments of new production techniques influence adoption behaviour. Bond and Wonder (1980), Quiggin (1981), Bardsley and Harris (1987) found risk aversion to be a prevalent attitude amongst Australian farmers. The growing of oilseeds, as with other crops, is a risky proposition as farmers face a variety of price, yield and resource uncertainties. The perceived riskiness becomes more important for radically new crop varieties about which producers have little knowledge.

Hardaker and Ghodake (1984) have shown the effect of risk attitude on the choice of technology or farming system in semi-arid India and further provided support for the existence of a relationship between absolute risk aversion and the certainty equivalent of expected income. If the new technology is perceived by the producer as 'too costly', then it is unlikely to be adopted. Costly is loosely applied here not only to imply dollar value but also riskiness in consonance with the Makeham and Malcolm (1993) assertion that all risk (or avoidance of risk) has some associated costs. These costs are linked to the lack of requisite skills and experience in the application of the new technology. The process of information transfer between researchers and farmers thus takes on major significance.

Rogers (1983) defines the adoption process as 'the mental process through which an individual passes from first hearing about an innovation to final adoption'. However, Feder et al. (1982) indicate that a more precise quantification is required and so distinguish between farm-level adoption and aggregate adoption. Aggregate adoption is the rate of adoption associated with a district, region or country. Farm-level adoption is defined as, 'the degree of use of a new technology in long-run equilibrium when the farmer has full information about the new technology and its potential'. Generally, risk-averse farmers tend to exhibit caution in adopting new farming techniques even when trials show that the innovation is worthwhile. By virtue of their aversion to risk, such farmers will usually have a preference for enterprises that they and neighbours have found to be 'reliable' through their own experience.

Plain et al. (1981), noted that a feature of 'new crops' which plays a significant role in their adoption by farmers is the risk relative to more traditional activities. A 'new crop' is favourable for a risk-neutral producer if its expected gross margin is higher than that of a competing crop. A risk-averse producer is also additionally interested in the distribution of the expected gross margin of a new crop and with the stochastic dependence that may exist between the new crop and present activities.

The adoption of a new crop such as Linola involves certain subjective risk (imperfect information) in that yields and prices, for instance, are more uncertain (as far as the farmer is concerned) than for other previously cultivated crops. There are also objective risks (variability) as the result of weather variations, disease outbreak or drought. In consequence, new techniques of production will be adopted only if they are consonant with the beliefs, goals and resource constraints of the individual farmer.

Applied agricultural research can only be regarded as possessing some potential value when it results in new farming practices which farmers can be persuaded are more stochastically efficient relative to prevailing practices. To be beneficial, new practices proposed by agricultural researchers have to be risk-efficient options for producers. This theme will be taken up in greater detail later in this chapter. As previously noted, risk-efficiency of new technologies can only be properly assessed by considering their impact on overall, not just partial, farming risk.

The assessment of new production methods by economists, in the main, should be based on ultimate farmer goals, attitudes, objectives and preferences as well as being relevant in terms of the farming environment. In this regard, whole-farm modelling approaches have been widely applied to assess new production technologies since, according to

Hardaker (1979), the approach has merit in its ability to allow simulation of farmer behaviour under different production environments. Dillon (1976) suggests that the whole-farm approach allows a more holistic or systematic view of technology testing and adoption. Mathematical programming, program planning, budgeting (partial or complete) approaches may be used in the whole-farm approach for technology assessments. However, as indicated by Anderson and Hardaker (1979), mathematical programming approaches in combination with some intuition are often the preferred option.

Given the recognised dynamism and unpredictability of the farming environment, the decision making process about the committment of scarce farm resources is important. Much of the rest of this chapter deals with issues relating to the elements of decision making under uncertainty. The discussion is focussed on the notion of subjective probabilities and utility that are important aspects of the decision about whether or not to adopt a new technology into the farming system.

3.3 Planning under uncertainty

Planning and decision making in agricultural production require some commitment to efficiency for the attainment of desired long-run goals. Prevailing uncertainty in the production environment, however, complicates decision making and increases the difficulty involved in selecting a farm plan consonant with production objectives given the uncertainty in consequences which often appear seemingly innocuous (Anderson 1996).

As earlier noted, farmers are regularly presented with situations requiring choice between several alternatives with uncertain outcomes. Decisions need to be made concerning production techniques and allocation of scarce resources of land, labour and capital. While some choices are made rather habitually in *ad hoc* fashion, others require in-depth evaluation of the consequences of each selected alternative because of the long-term ramifications of these decisions for farm profitability and financial viability.

A decision problem exists when a given individual has alternative choices, each with significant consequences or payoffs attendant to its selection. The decision of concern in this study is the choice of a new technology (Linola) over conventional technology.

According to Anderson et al. (1977), when uncertainty exists such a decision problem becomes a risky one. Five basic components of decision making under uncertainty have been specified by Nelson et al. (1978) as: 1) choices; 2) events; 3) outcomes; 4) probability of occurrence of events; and 5) decision rule for evaluating choices. A generalised symbolic representation of the elements of a decision problem is provided in Table 3.1. The elements, $A_1,A_2,...,A_n$, are the decision alternatives each of which is associated with $S_1,S_2,...,S_m$, states of nature. In the body of the table, $Y(A_1,S_1),...,Y(A_n,S_m)$, represent the payoffs - outcome of selecting a decision option - associated with each decision option and state of nature. Based on this representation, arriving at a decision requires a decision criterion for ordering the feasible alternatives, A_i, and also some knowledge of the probabilities of occurrence, $P(S_i)$, of each possible state of nature such that $\Sigma_i P(S_i) = 1$. However, as noted by Anderson et al. (1977), by the nature of uncertainty, a good decision consistent with the decision maker's expectations and preferences, does not necessarily guarantee a good outcome.

Table 3.1 : Symbolic representation of the elements of a risky decision problem

States of nature	Alternatives			
	A_1	A_2	. . .	A_n
S_1	$Y(A_1,S_1)$	$Y(A_2,S_1)$	. . .	$Y(A_n,S_1)$
S_2	$Y(A_1,S_2)$	$Y(A_2,S_2)$	. . .	$Y(A_n,S_2)$
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
S_m	$Y(A_1,S_m)$	$Y(A_2,S_m)$	. . .	$Y(A_n,S_m)$

3.3.1 Risk, uncertainty and utility

According to Robison and Barry (1987), if an individual is able to specify the outcome of an event with insignificant doubt, he/she faces certainty. However, if an individual possesses insufficient knowledge to specify a unique outcome for an event, then that individual faces uncertainty.

Makeham and Malcolm (1993) noted that risk is a major factor in agricultural production in Australia since it influences the choices made by a farmer amongst competing alternative courses of action. Proper management of risk in agricultural production requires prior identification of prevailing sources of risk within a particular production environment. Officer, Halter and Dillon (1967) emphasised that the explicit recognition of the importance of risk would result in the modification of many planning recommendations and so increase the likelihood of their adoption. As depicted in Figure 3.1, the farmer necessarily has to form predictions/expectations about the future, choose and implement plans consistent with these expectations and stand ready to accept the consequences of planning decisions - whether favourable or unfavourable.

According to the Chambers dictionary (1993), risk is defined in probabilistic terms as, ' ..."chance" which implies a possible but not deterministic outcome'. Rowe (1977) has defined risk as the potential for unwanted, negative consequences of an event or activity. Wasserman and Wasserman (1979) define risk as, 'the possible occurrence of an event that produces adverse effects on man and his environment. The degree of risk is related to both the probability of occurrence and to the estimated outcome in terms of nature, intensity and duration of the adverse effects'. In like fashion, Gratt (1987) proposed risk to be 'the potential for the realisation of unwanted, adverse consequences to human life, health, property or the environment'. And Shrader-Frechette (1985) believes risk to be 'a compound measure of the perceived probability and magnitude of adverse effect'. These latter definitions, however, ignore the possibility that risk can also be a good outcome forgone. A more circumspect Stiglitz (1974) likens risk to love - a word that defies any precise definition. A seemingly more robust definition is that used by the Australia-New Zealand standard that risk is, 'the chance of something happening that will have an impact upon objectives. It is measured in terms of consequences and likelihood'. Or the more succinct 'uncertainty in consequences', used by Hardaker et al. (1991).

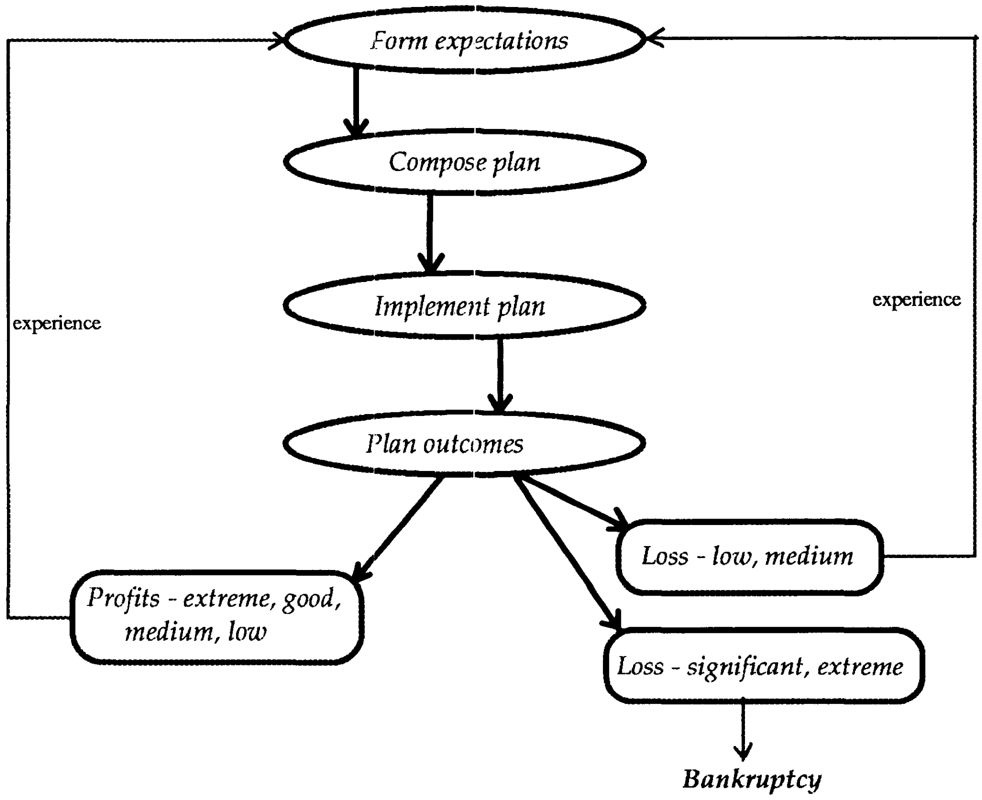


Figure 3.1 : Expectation, choice and outcome

Quiggin and Anderson (1990) differentiate between downside risk - expected value of negative consequences - and pure risk - deviations in consequences (outcomes), whether positive or negative, from their expected values, and indicate the desirability of accounting for both risk types in farming systems. In this work, risk and uncertainty are used interchangeably mainly for reasons of convenience. In the manner of Boisvert and McCarl (1990), no attempt has been made to distinguish between the two concepts on the basis of the degree of knowledge about the probability distributions (e.g., Knight 1921), nor is risk explicitly considered as a subset of uncertain events whose outcomes affect the decision maker's well-being (Robison and Barry 1987).

Sonka and Patrick (1984) suggested that production or technical risk is the random variability inherent in the production process on a farm. Weather, diseases and pests are major sources of risk in livestock and crop production that create variability in yields. Market risk is also a major source of risk in farming since farmers are price takers. Consequently, risk influences agricultural production mainly through yield and/or price uncertainty (Dillon and Anderson 1990). Short-run fluctuations in input and product prices can result in significant shortfalls in farm income. The variability of inflation and interest rates is also a significant source of risk influencing long-run farm production decisions. In this study, it is assumed that product price and yield risk are the main contributors to the uncertainty of farm income. Furthermore, following the Dillon (1977) argument that prices of controlled variable inputs are known at the time of decision making about their levels, input prices in this work are regarded as deterministic. Generally, the analysis of the farmers' decisions under these conditions of price and yield uncertainty is based on the knowledge of their attitudes to and perceptions of risk. However, in connection with a new technology, much of the risk arises as a result of imperfect knowledge. Under conditions of imperfect knowledge, there is no 'correct' measure of risk, and in consequence, individual perceptions or beliefs become paramount in the analysis of the decision making process.

3.3.2 Bernoulli principle

The Bernoulli principle or expected utility theory (EU), ascribed to Daniel Bernoulli (1738), provides a unique criterion for ranking risky alternatives by considering the preferences - 'utility' and 'preference' are often used interchangeably - and beliefs of the decision maker. Bernoulli postulated that decision makers, rather than seeking to maximise the expected monetary value of risky prospects, assign 'moral expectation values' or utilities to the outcomes.

The basic utility theory as proposed by Bernoulli and later demonstrated by Ramsey (1931) and extended by von Neumann and Morgenstern (1947) and Savage (1954), is based on the assumption that the worth of an extra dollar is not identical to a rich and a poor person. The behavioural axioms on which the expected utility theory rests have been postulated in a variety of ways in the literature since the landmark works of von Neumann and Morgenstern (1947), Friedman and Savage (1948), Savage (1954) and Luce and Raiffa (1957). However, Dyckman et al. (1969) provide one of the more comprehensible treatises on the subject.

The Neumann-Morgenstern axioms are ordering, transitivity, continuity and independence. Summarily stated, the ordering axiom requires that any decision maker having two choices, A_1 and A_2, will either prefer A_1 to A_2, A_2 to A_1 or will be indifferent between them; transivity implies that for a decision maker with a third choice of A_3, if A_1 is preferred to A_2, and A_2 preferred to A_3, then A_1 is preferred to A_3; the postulates of continuity and independence require that if A_1 is preferred to A_2 and A_3 is any other prospect, then the individual will prefer a mix of A_1 and A_3 to the same mix of A_2 and A_3.

Following from the axioms, the Bernoulli principle implies that for an individual whose preferences do not violate the reasonable axioms of ordering, transitivity, continuity and independence, a unique utility function exists that is a reflection of the individual's preferences for the available risky prospects (von Neumann and Morgenstern 1947; Anderson et al. 1977; Dillon 1979). Consequently, a decision maker should normally select between risky prospects with the aim of maximising expected utility.

As noted by Anderson et al. (1977), the Bernoulli principle implies a unified theory of utility (preference) and subjective probability (degree of belief). Dillon (1979) also noted that Bernoullian choice under uncertainty implies both personal degrees of preference and also belief. This is the basis of the subjective expected utility hypothesis (SEU), a logical extension to the EU by Ramsey (1931), Savage (1954) and Pratt, Raiffa and Schlaifer (1964). The essential difference between EU and the SEU is that, with the latter, probabilities of outcomes are not necessarily objectively known. In contrast, EU assumes knowledge of the probabilities of outcomes. The SEU hypothesis implies that choices made under conditions of uncertainty should be governed by the decision maker's preferences and beliefs. Therefore, a decision maker is assumed to pursue objectives that enhance the utility obtained from each identified decision option based on his/her perception of the risks involved.

Mathematically, the goal of SEU is the representation of preferences over options by some numerical index of utility, U, and a probability measure, P, on the possible states such that an option, say A, is preferred to another option, say B, only if the SEU of A is larger than that of B. i.e.,

$$\mathrm{SEU(A)}=\sum_{s} P(s)U(A_s) > \mathrm{SEU(B)}= \sum_{s} P(s)U(B_s) \qquad [3.1]$$

where,

$P(s)$ = subjective probability of the state, s

A_S, B_S = outcome of option A, B when state s occurs

$U(A_S)$, $U(B_S)$ = utility value of outcome A, B with occurrence of state s.

The concept of utility or preference is fundamental to decision making under uncertainty. Utility can be applied as a measure of a decision maker's rational evaluation of the total worth of a specific outcome. Rationality describes the process by which the decision maker selects the best possible alternative within the constraints posed by his/her preferences and constraints, without regard to what decision making process is used (Roumasset 1979). The notion of rationality is, therefore, a feature of full-optimality decision models which Bernoullian models are regarded as. Rational choice within the SEU-construct is subjective implying that the basis of rational decisions under uncertainty are decision-maker value judgments. For this reason, individual preference or utility functions become important. More importantly, however, in the context of this study, are subjective probabilities or beliefs that producers hold concerning the profitability a new oilseed crop, Linola.

Selly (1984), has observed that the behavioural axioms of the SEU are not the only set of possible axioms for risky decision analysis. Kahneman and Tversky (1979) developed a set of axioms for their prospect theory using the notion of probability preference functions. They demonstrated that behaviour which appears to be inconsistent with SEU is consistent with their theory. Quiggin (1986,1993) also proposed an axiom-based anticipated or rank dependent utility hypothesis which is suggested to be consistent with the transitivity axiom and the preservation of dominance. More recently, a re-engineered normative-cum-descriptive expected utility hypothesis has been proposed by Hertzler (1995) based not on the N-M utility function of wealth but on consumption and time preference.

However, the question of whether the SEU or Kahneman-Tversky prospect theory or the Quiggin anticipated utility hypothesis or Hetzler's revised EU theory will better serve the purposes of the researcher in specifying decision rules and predicting producer behaviour under uncertainty remains conjectural. Battalio, Kagel and Jiranyakul (1990) have shown that no single option consistently organises choices.

However, as noted by Buschena and Zilberman (1994), the SEU approach is an appropriate normative tool for risk management.

Although Allais (1953), Kahneman and Tversky (1979) and Machina (1987) have at different times shown that individuals sometimes make decisions inconsistent with the SEU hypothesis, the construct remains the basis of most work on risky decision analysis. Pratt (1974) argues that it is the only rational approach and, according to Hertzler (1995), any eulogies for the SEU decision theoretic approach are premature. Thus, since, as observed by Schoemaker (1982), Anderson (1996) and Hardaker et al. (1991), no better operational framework for decision making under uncertainty has yet been widely accepted, the SEU is the choice criterion elected for use in this work.

3.3.3 Calibration of uncertainty

The formulation of expectations about the probability of occurrence of uncertain events is central to risky decision making. Anderson (1976) has observed that setting parameters at their mean values and seeking 'correct' deterministic, risk-indifferent solutions is feasible only under extremely restrictive and generally unacceptable conditions. According to de Finetti (1972), the best way of describing the inexplicable, the unpredictable and the malrepresented is through the calculus of probability. Anderson et al. (1977), in agreement with Savage (1954), have stated the concept of probability as being the logical relationship between a proposition and a body of evidence and have posited further that the only types of probabilities useful in decision analysis are subjective ones. According to Winkler (1972), the concept of subjective probabilities is a pivotal one in statistical decision theory or Bayesian statistics.

Probability distributions are a description of the stochastic behaviour of random variables. Subjective probabilities are beliefs held by individuals concerning an event that reflect their perception of the uncertainty associated with the event. Anderson and Dillon (1992) have argued that farmers' beliefs about uncertain outcomes may be encoded as subjective probabilities implying that a probability distribution is definable for the consequences of each available alternative. These beliefs are essential to decision making under uncertainty in the context of the SEU hypothesis and are applicable to both unique and repetitive events (Dillon 1971). According to Bessler (1981, 1984), the sole normative criterion applied to these individual beliefs is that they are coherent, meaning that they are not inconsistent or contradictory. Anderson et al.

(1977), drawing on the concepts developed by Savage (1954), indicate that subjective or psychological probabilities must be consistent with the axioms, rules and calculus of probabilities. Accepting the basic axioms around which probability calculus devolves, then the probability that a set of mutually exclusive and independent random events occurs is the sum of their respective probabilities subject to the condition that the probabilities do not sum greater than unity.

Generally, a decision maker's degree of belief should change as his/her experience and knowledge increase. For this reason, it is to be expected that different decision makers with a store of common experiences would have degrees of belief that closely correspond (Anderson et al. 1977). Subjective probabilities can not be right or wrong though it is to be expected that a rational decision maker would seek refinement of his/her beliefs to account for new information and to eliminate or minimise any biases that may arise from misrepresentations of the information available to him/her.

For the present work, the elicited subjective probability distribution of the possible outcomes are assumed to be a measure of the uncertainty associated with the available choice options as perceived by the studied farmers. Therefore, credible methods of eliciting probabilities from agents involved in the development and adoption of Linola are needed for this study. Anderson et al. (1977) and Bessler (1984) have outlined several methods for eliciting probability judgments. These include the visual impact, triangular distribution and judgmental fractile methods.

The visual impact or strength-of-conviction method involves providing the subject with a visual aid to assist with the quantification of his/her subjective beliefs about given risky prospects. With this approach, the possible range of the uncertain event is elicited and divided into a convenient number of mutually independent intervals to which the subject is then invited to apportion counters according to his or her strength of conviction. The allocations are revised until the subject expresses satisfaction with the displayed distribution. The ratios of the observed class frequencies to the total number of counters provide an indication of the probabilities of the relevant intervals. The subject's cumulative distribution function (CDF) can consequently be plotted using this information.

The judgmental fractile method does not employ any explicit motivational procedure but involves direct assessments of a subject's CDF by successively obtaining equally likely probability intervals (Raiffa 1968). This is based on the assumption that the subject can easily translate his/her true beliefs into stated beliefs using the ethically neutral 0.5 probabilities. The method begins with the assessment of the two extreme fractiles at probability zero and one. Next the 0.5 fractile is determined via a 50:50 gamble that the probability of the unknown event is greater than or less than 0.5. The procedure continues in similar fashion, by continually sub-dividing previously determined intervals into equally likely parts for the 0.75, 0.25, 0.125, etc., fractiles. From the resultant information, a smooth CDF can be drawn through the obtained points.

The triangular distribution method of eliciting subjective probabilities requires less information to estimate the probability distribution and thus is simpler to use, though possibly less accurate. The method involves specification of the lowest possible value, the highest possible value and the mode or most likely value. The triangular distribution is fully defined by these three values, from which any required statistics can be calculated. Despite recognition of the fact that the approach restricts the form of the probability distribution somewhat, its use is still recommended (Cassidy et al. 1970; Anderson et al. 1977; Chee Yoong 1978; Anderson and Dillon 1992). Given that the choice of a universally appropriate technique for estimating individual probability judgments remains inconclusive, any of the methods applied should be definite, consistent and logical, according to Cassidy et al. (1970). Because it is logical and consistent as well as easy to apply in the particular conditions of this study, the triangular distribution approach was chosen for use.

In as far as misconceptions and misrepresentations can lead to biases in probability judgment (Anderson et al. 1977), they need to be taken into consideration in the elicitation process. Tversky and Kahneman (1975) and Anderson et al. (1977) have indicated that the main sources of biases in probability judgments by individuals are anchoring and representativeness.

Anchoring is the phenomenon whereby events close to some initially chosen event are overemphasised. The anchoring effect results from the difficulty experienced by most people in moving away from some value, usually a mean or modal value, that first occurs or is suggested to them during the elicitation process. Anchoring on this value may lead to assessed probability distributions that have too small a variance according to Anderson et al. (1977). The effect of anchoring may be reduced by encouraging the subject to consider as starting points extreme values of the distributions as was done with the respondents in this study.

Generally, individuals display a tendency to base probability judgments on assessment of the degree of similarity or representativeness of sample information to the class to which it is correlated, i.e. particular characteristics of an event are selectively over-emphasised. However, as noted by Anderson et al. (1977), while representativeness may be considered a relevant clue in the forming of probability judgments, the danger exists that undue emphasis is placed on it to the exclusion of other types of evidence. This may lead to the neglect of prior probabilities, misconceptions of chance and disregard of predictive accuracy. Usually, comparison of inter-related beliefs will often bring inconsistencies to the fore which can then be corrected to reduce any bias in elicited probability judgments.

3.3.4 Risk attitudes

One of the fundamental concepts of risky decision theory is the decision maker's attitude to risk which may be inferred from the shape of his/her utility function. In principle, a decision maker's utility function may be linear, concave or convex, respectively, implying risk neutrality, risk aversion and risk preference. Whilst the possibility exists for the same individual to have a combination of these shapes for different ranges of payoffs, in practice, risk aversion is the norm. Simply defined, aversion to risk is a preference for certainty over uncertainty. Generally, therefore, risk aversion implies that decision makers faced with risky prospects will select relatively riskier alternatives only if they have higher expected returns.

As noted by Robison et al. (1984), the magnitude of the second derivative cannot be used for interpersonal comparisons of risk aversion because an individual's utility function is only unique up to a positive linear transformation. Pratt (1964) and Arrow (1974) suggested a measure for inter-personal comparisons of utility at identical wealth levels now commonly called the Pratt-Arrow coefficient of absolute risk aversion (r_a). Generally, utility is specified in terms of wealth, w, and the utility function assumed to be monotonically increasing, i.e., $U'>0$, reflecting a positive marginal utility for wealth. The r_a for a decision maker with initial wealth, w, is the negative ratio of the first and second derivatives or the bending rate of his/her utility function. That is,

$$r_a(w) = -U''(w)/U'(w) \qquad [3.2]$$

A related measure of risk aversion is the relative risk aversion (r_r), given by:

$$r_r(w) = -wU''(w)/U'(w) \quad [3.3]$$

from which it may be deduced that:

$$r_a(w) = r_r(w)/w \quad [3.4]$$

Anderson (1973a) and Dillon (1979) have argued that, if a one-period utility function for w is acceptable, then the use of money gain or loss instead of wealth should closely approximate the utility function around a specified wealth position.

In contrast to the utility function, which is only unique up to a positive linear transformation, r_a and r_r are not affected by linear transformations of the utility function and so allow inter-personal comparisons. The signs are an indication of the risk attitude of the individual - positive for risk aversion, negative for risk preference and zero for neutrality - and, for positive values, the magnitude of either coefficient increases with the degree of risk aversion. These measures are commonly used in empirical work in risky decision analysis. As noted by Robison et al. (1984), since r_a and r_r are functions of wealth, they can be employed to test hypotheses about responses of risk aversion to changes in wealth or other objects of utility.

3.3.5 Individual preference measurements

A prerequisite for the determination of a utility-maximising farm plan is the knowledge of the relevant farmer's utility function. As noted by Boisvert and McCarl (1990), when preferences for risk are known and can be precisely specified as a utility function, maximising expected utility should generate a unique and complete ordering of alternative farm plans. However, preferences are rarely known and are difficult to measure in applied decision analysis.

Risk attitudes may be captured via suitably elicited utility functions. The elicitation of preference or utility functions of decision makers is usually based on a gambling approach aimed at identifying certainty equivalents for stipulated gambles or lotteries. A certainty equivalent is the amount exchanged with certainty that makes the decision maker indifferent between this exchange and some specified risky prospect (Anderson et al. 1977).

There are several alternative approaches for eliciting individual preferences as reviewed by Officer and Halter (1968), Anderson et al. (1977) and Bessler (1984). Utility functions normally relate the outcomes of choice to single-valued indices of desirability and so can be thought to represent decision-maker preferences (Robison and Barry 1987). The most commonly used methods for the elicitation of decision-maker preference functions are the Neumann-Morgenstern (N-M) approach (von Neumann and Morgenstern 1947), the equally likely certainty equivalent (ELCE) or the modified N-M approach and the equally likely risky outcome (ELRO) or Ramsey method (Ramsey 1964). These methods involve time-consuming direct personal interviews applying, sometimes, complex concepts. Consequently, in many instances of empirical work, the approaches may not always be practical in terms of getting the subject of the interview to understand what the 'game' is about.

An alternative approach for the measurement of decision-maker preferences is described by King and Robison (1981). The approach involves applying information revealed by decision-maker choices from carefully selected outcome (payoff) distributions to delineate lower and upper bounds on the decision maker's absolute risk aversion function. The procedure which uses the evaluative criterion of stochastic dominance with respect to a function (SDRF), is based on the notion that, under certain conditions, the choice made between two narrowly defined distributions divides absolute risk aversion space over that range into a region consistent with the choice made and another that is not (Meyer 1977a; McCarl 1990). Wilson and Eidman (1983) conducted an empirical test of the interval approach using swine producers in Southern Minnesota and concluded that the approach is low cost and avoids interviewer bias.

Due to the particular circumstances of this work and financial limitations of the author, the interval approach was chosen for use in this study. A detailed discussion of the procedure as applied in this study is provided in the next chapter.

3.4 Decision rules

Under conditions of uncertainty, the whole gamut of possible outcomes needs to be scrutinised and evaluated on the basis of decision-maker preferences. However, individual preferences are typically difficult to determine. When individual preferences cannot be fully specified, risk efficiency analysis (REA) becomes an alternative approach (Boisvert and McCarl 1990).

Risk efficiency analysis (REA), though based on the maxim of SEU, as previously defined, does not require full specification of the decision-maker utility function. As a consequence, the application of REA requires the definition of an efficiency criterion. An efficiency criterion is a decision rule that results in the partial ordering of the choices of decision makers whose preferences correspond to certain limitations placed on the utility function (King and Robison 1981). For some risky prospect A to be preferred to another risky prospect B, based on the defined efficiency criterion, prospect A must be known to have a greater expected utility than B given the limitations imposed on the utility function. A decision option is said to be dominated in risk-efficiency sense if there is some other option that is superior given the restrictions imposed on risk preference. Only those options that are not dominated are regarded as risk efficient and it is from this set that a decision maker whose utility function meets the required conditions will find his or her most preferred option.

A number of different risk efficiency rules have been proposed in the literature, as discussed below.

3.4.1 Expected value-variance analysis

The easiest and most widely applied risk efficiency analysis criterion is the expected value-variance (or mean-variance, EV) analysis first applied by Markowitz (1952) as a criterion for portfolio selection. The EV criterion is based on the hypothesis that, when presented with two distributions with equal means, a risk-averse decision maker will always prefer the distribution with the lower variance.

The EV model is consistent with the expected utility hypothesis under certain restrictive assumptions of either quadratic utility or normally distributed returns (Tobin 1958; Tsiang 1972; Porter 1973). These restrictions have made its application in empirical analysis contentious (Robison and Barry 1987).

3.4.2 Stochastic efficiency

Another commonly used efficiency criterion is stochastic dominance analysis. Stochastic dominance analysis provides a means of selecting a set of efficient alternatives, based on the EU theory, for some specified set of utility functions. Because stochastic dominance places few restrictions on the utility function and none on the probability distribution, it has certain theoretical advantages over such criteria as EV (Boisvert and McCarl 1990).

Stochastic efficiency enables partial ordering of risky prospects without the need for exact representations of decision-maker preferences. These criteria can be appraised by how well their inherent assumptions about preferences conform with actual preferences, their discriminatory power and by the ease with which they can be applied in problems involving many risky prospects.

Hadar and Russell (1969) and Hanoch and Levy (1969,1970) developed generally applicable efficiency criteria referred to as stochastic dominance rules. These criteria require the pairwise comparison of CDFs. For any two risky prospects F and G, G stochastically dominates F if the expected utility under G is at least as high as that under F for all utility functions in a specified set (King and Robison 1984).

First-degree stochastic dominance (FSD) applies to decision makers having positive marginal utility for the attribute under consideration, implying a preference for more to less. In essence, the only restriction on the utility function is that the first derivative is positive, $U'(y) > 0$. Since no bound is placed on the absolute risk aversion function, r_a, its value may lie anywhere between positive to negative infinity,

$$-\infty < r_a < \infty.$$

In graphical terms, a dominant CDF lies nowhere to the left and at least somewhere to the right of a dominated CDF. For normal distributions, this can only occur with identical variances and different means. In reality, very few distributions can be eliminated by such a broad efficiency criterion. Especially when there are many alternatives to be ordered, FSD may not be a satisfactory criterion.

Greater discriminatory power is obtained by the additional condition of second degree stochastic dominance (SSD) that the second derivative of the utility function is negative ($U''(y) < 0$) (Fishburn 1964; Hadar and Russell (1969; Hammond 1974). This implies that the decision makers are risk averse. With normally distributed outcomes, SSD equates to the mean-variance (EV) efficiency criterion (Anderson 1975; King and

Robison 1984). Despite its greater discriminatory power relative to FSD, SSD still may not significantly reduce the number of available options. Additionally, as King and Robison (1981) have demonstrated, agricultural producers at times exhibit increasing marginal utility over certain outcome ranges.

Third degree stochastic dominance (TSD) proposed by Whitmore (1970) and Hammond (1974) imposes further restrictions on the utility function to increase the discriminatory power of the efficiency criterion. Third degree stochastic dominance holds for individuals whose risk aversion decreases with increasing wealth ($U'''(y) > 0$). Thus, TSD implies that decision makers show a preference for positive skewness in distributions of returns (Anderson et al. 1977). However, despite the added restrictions, the discriminatory power of TSD in ordering risky alternatives relative to SSD is yet to be demonstrated as significant. Anderson (1974,1975,1979) and Anderson et al. (1977) have counselled that the added cost of TSD may not cover the marginal benefit of identifying only a slightly smaller efficient set of plans.

3.4.3 Stochastic dominance with respect to a function

Generalised stochastic dominance or stochastic dominance with respect to a function (SDRF) is an efficiency criterion which establishes sufficient conditions for the distribution of outcomes defined by the cumulative distribution function $F(y)$ to be preferred to the outcomes defined by another cumulative distribution function $G(y)$ by all individuals whose absolute risk-aversion function lies between the bounds $r_1(y)$ and $r_2(y)$ (Meyer 1977a,b; McCarl 1988; Raskin and Cochran 1986b) It is a logical extension of SSD which can significantly reduce the number of options in the efficient set of plans, depending on the range of risk aversion used.

The absolute risk-aversion function, as previously noted, measures the degree of convexity or concavity of $U(y)$, and so provides an indication of the risk attitude of the decision maker - whether risk-preferring or risk-averse.

In effect, the upper (r_2) and lower (r_1) bounds on a decision maker's absolute risk aversion function define an interval which represents decision-maker preferences (King and Robison 1981). Thus, a lower and upper bound may be defined for r_a such that,

$$r_1 < r_a < r_2$$

As noted by King and Robison (1981), the less flexible efficiency criteria such as FSD and SSD can be regarded as special cases of SDRF. Stochastic dominance with respect to a function is therefore an efficiency criterion that allows greater flexibility in the representation of individual preferences. Meyer (1977a) has developed a solution procedure that requires the identification of a utility function, U, that minimises

$$\int_{-\infty}^{\infty} [G(y) - F(y)]\, U'(y)dy \qquad [3.5]$$

subject to

$$r_1(y) \leq -U''(y)/U'(y) \leq r_2(y) \qquad [3.6]$$

If, for a certain class of decision makers, the minimum difference of the above expression is positive then the distribution *F(y)* is unanimously preferred to *G(y)*, implying that the expected utility of *F(y)* is greater than that of *G(y)* for all decision makers in that class. If the minimum is zero, a decision maker within the specified group may be indifferent between the two distributions which, consequently, cannot be ordered. If the minimum difference is negative, however, then *F(y)* cannot be unanimously preferred to *G(y)*. To test for preference in this instance, expression 3.5 above is reversed thus:

$$\int_{-\infty}^{\infty} [F(y) - G(y)]\, U'(y)dy \qquad [3.7]$$

A positive minimum difference would then mean that *G(y)* is preferred to *F(y)*. If the minima of both equations 3.5 and 3.7 are non-positive then neither distribution is unanimously preferred by the decision makers under consideration (Raskin and Cochran 1986). In such an instance, the SDRF criterion cannot then be used to order these two alternatives.

King and Robison (1984) have observed that the generality of an efficiency criterion and its discriminatory power are linked. Specific restrictions placed on utility functions define a class of decision makers for whom the specified decision rule applies. In general, increasing the discriminatory power of a decision criterion by imposing greater restrictions on the utility function also tends effectively to decrease the number of decision makers to which the rule is applicable. This obvious trade-off between discriminatory power and generality needs to be considered in selecting a range for a given decision setting. At one extreme is FSD which places little restriction on decision-maker preferences and consequently has low discriminatory power despite wide applicability. In contrast, SDRF, which is more discriminating, imposes greater restrictions on decision-maker preferences and consequently may have less general application although more useful results are likely to be obtained. Various agricultural applications of SDRF include for example, Kramer and Pope (1981), King and Robison (1981), Pederson (1984) and Harris and Mapp (1986).

The discriminatory power of SDRF is dependent on the values specified for r_1 and r_2 as demonstrated by King and Robison (1981) and Bardsley and Harris (1987). Thus, application of SDRF for an individual requires specific information concerning the lower and upper bounds of a decision-maker's absolute risk aversion function. King and Robison (1981) have suggested a protocol for eliciting r_1 and r_2 that uses information revealed through a series of choices between carefully selected distributions. The preference interval measurement procedure as used in this study is later detailed in Chapter 4.

There are other efficiency criteria that have been applied in mathematical programming models other than those consistent with the EU maxim. The most widely applied of these generally ad hoc criteria include safety-first analysis (Roy 1952, Kataoka 1963, Low 1974), expected gain-confidence limit analysis (Baumol 1963) and the maximin and minimax analysis (Hazell and Norton 1986).

3.5 Mathematical programming in farm planning

Economic production theory is mainly concerned with the maximisation of benefits or the minimisation of costs. Any problem entailing the maximisation or minimisation of some numerical function of one or more variables (or functions) subject to certain specified constraints is an optimisation problem. Optimisation is a term that Hadley (1962) suggested is applicable to this class of constrained problems in production theory. For unconstrained maximisation problems where the objective is the determination of the 'best' point on the firm's production function, differential calculus can be applied.

Since the technique of linear programming was first proposed late in the fourth decade of this century, there has been interest in a group of optimisation problems called programming problems which are not amenable to methods of differential calculus. Such problems may occur in government, military tactical planning, agriculture, commerce and industry.

In economics, programming problems are usually concerned with the efficient allocation of scarce resources for some productive endeavour. Mathematical programming involves the use of mathematical models in an attempt to solve such problems regarding the optimal allocation of scarce resources between competing ends whilst allowing assumptions about behaviour to be built into the model in the assumed objective function and constraints. The mathematical expressions characterising a given model may be linear or non-linear in form and may have continuous or discrete variables. When the variables in the model are assumed known with certainty, it is considered a *deterministic* model, but when the variables are subject to random variation then the model is *stochastic*.

While mathematical computations cannot fully represent the complexities of the real world - being only abstractions thereof - they can, however, be of some value in the decision making process associated with the general realm of production economics by providing indications of the potential ramifications of the feasible options that may be available to the decision maker. The identification of optimal decisions requires that the decision maker pursues well-defined goals in carrying out activities. An optimal decision is one that the decision maker thinks best fulfils the decision maker's set of goals. The use of mathematical programming as a basis for solving a decision problem means that, as a first step, relevant variables need to be identified that are proxies for the decision maker's explicit goals and for which his/her preferences may be recognised.

3.5.1 Linear programming

Although the origins of mathematical programming date back to the theories of linear and non-linear equations, George Dantzig is usually credited with developing the linear programming (LP) technique - a procedure by which a single economic (efficient) optimum can be identified amongst numerous feasible alternatives - whilst working on problems of military logistics during the second world war. Dorfman et al. (1958, p.4) have described the technique as a flexible and powerful tool for economic decision analysis and have found many significant applications in the area.

A wide range of real decision problems, including agricultural ones, have been shown in the literature to be amenable to solutions by LP techniques (e.g., Heady and Candler

1958; Charnes and Cooper 1961; Davis 1967; Little and Wooten 1972; Gaither 1975; Craig et al. 1979; Boisvert and McCarl 1990; Jeffrey, Gibson and Faminow 1992).

The basic LP formulation allows the selection from an array of alternatives of that alternative (or alternatives) which is both feasible and achieves explicit decision objectives. It involves the maximisation or minimisation of a *linear* objective function subject to a set of linear resource constraints and non-negativity restrictions on the variables.

The basic LP formulation may be represented by,

$$\max \quad z = \sum_{j=1}^{n} c_j x_j \qquad [3.8]$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad (i = 1, \dots, m) \qquad [3.9]$$

$$x_j \geq 0 \qquad (j = 1, \dots, n)$$

where a_{ij}, b_i and c_j are known constants and x_j is the activity level.

In whole-farm planning, the LP approach allows the systematic effects of different resource allocation prescriptions to be determined. According to Barnard and Nix (1979), full utilisation of major resources in a solution and low marginal value products implies that an apparently sound balance has been achieved between the different resources with regard to the available opportunities.

Computerisation means large and complex models are solvable without having recourse to questionable simplifications of underlying input and output relationships and minimal risk of computational errors. LP computer routines today include sensitivity analysis which provides answers concerning the stability of the solution. Methods of sensitivity analysis include ranging and parametric programming.

Linear programming is, however, restricted in its application as a result of the limitations posed by the underlying assumptions of the technique as may be gleaned from texts on the subject including Heady (1954), Dantzig (1963), Beneke and Winterboer (1973), Barnard and Nix (1979), Gass (1984), Luenberger (1984) and Winston (1991). These are summarised as:

a) The assumption of constant linear input-output relationships. The linearity assumption clearly distorts what obtains in the real world given that estimated production functions are rarely linear; it violates the basic economic axiom of diminishing returns.

b) The assumption that all resources and activities are additive and divisible often raises problems in situations of joint costs or lumpy inputs. The additivity assumption usually presents few problems when the activities under scrutiny are related in a competitive or supplementary fashion. Problems may however arise when the relationship is complementary.

c) With the single-valued coefficients of LP, the technique is usually applied without taking risk and uncertainty into consideration though it is possible to take consider stochastic objective function values by using their expected values. It is also possible to include linear risk constraints, as in the MOTAD formulation, discussed below.

These assumptions are not only relevant to LP but to much of planning as a whole. It is consequently necessary to examine ways in which the modelling process can be modified to allow a fair representation of a given planning scenario. Thus, despite restrictive assumptions of linearity, divisibility, finiteness, additivity and single-valued expectations, LP remains a popular mathematical programming technique (Anderson et al. 1977).

Duloy and Norton (1975) and Anderson (1975) have noted that lumpy resources commonly found in agricultural production can be handled via integer programming and that separable programming algorithms or linear approximation via segmentation can be used to handle non-linearities. Several models, as discussed below, have also been proposed to allow incorporation of risk and uncertainty in linear programming formulations.

3.5.2 Non-linear programming

The assumption of linear relationships is, in many cases, an appropriate assumption for the range of values considered for a given problem. However, for some problems, the relationships between the variables of interest are non-linear and hence the true impression of the structure and interplay of the system under consideration can only be obtained by the construction of non-linear functional forms to represent the system.

Non-linear programming problems occur in a wide variety of disciplines including agricultural production. Non-linearities can arise in production functions, cost curves and almost all facets of problem formulation.

Mathematical algorithms for the solution of non-linear programming (NLP) problems which typically use specialised iterative procedures, have a more recent history than LP. The development of non-linear algorithms has followed the development of the computer which is required to handle the very heavy computational burden required to solve non-linear models of any size.

The general form of this class of problems may be written as:

$$\text{maximise/minimise } z = f(x_1, x_2, \ldots, x_n) \tag{3.10}$$

subject to

$$g_i(x_1, x_2, \ldots, x_n) \ (\leq, =, \text{or} \geq)\ b_i, \quad \text{for } i = 1,2,\ldots,m.$$

and

$$x_j \geq 0, \qquad \text{for } j = 1,2,\ldots,n$$

Expressed in this fashion, the problem is the maximisation/minimisation of a linear or non-linear objective function, f, comprising n decision variables which are subject to m linear or non-linear constraints, g_i ($\leq$, $=$, or $\geq$)b_i , and all decision variables, x_j, are usually restricted to be non-negative. However, several algorithms such as in GAMS/MINOS-5 (Murtagh and Saunders 1977) allow a free definition of variables allowing them to take on positive or negative values.

A class of NLP problems, which has been studied most extensively and is being widely used in whole-farm planning, is that in which the constraints are linear and the objective function is non-linear. A common form of this type of programming problem is quadratic programming which is specified as a quadratic objective function with linear inequality constraints. The quadratic formulation, which closely approximates more general formulations of expected utility problems (Levy and Markowitz 1979), arises from portfolio selection and constrained regression problems.

The portfolio model provides an appealing framework for analysing optimal enterprise combinations in agricultural production. The aim of portfolio analysis is to define the allocation of resources across an array of choice possibilities that maximises the decision maker's utility (Anderson et al. 1977). The approach is founded in micro-finance theory as discussed, for example, by Tobin (1958), Markowitz (1959) and Sharpe (1970). Its usefulness in decision analysis has been variously demonstrated by Tsiang (1972), Robison and Brake (1979), and Levy and Markowitz (1979). However, some limitations of the quadratic programming formulation are discussed later in this section.

For the present study, the problem has been formulated as a single-period, non-linear programming problem which is non-linear in objective function with linear inequality constraints akin to a portfolio selection problem.

3.5.3 Risk in programming models

Hardaker et al. (1991) have noted that the modelling of any risky farming system must commence with a proper understanding of the impacts of uncertainty on the system. Given that risk influences agricultural production largely through yield and/or price uncertainty (Boisvert and McCarl 1990; Dillon and Anderson 1990), activity net revenues in any programming model are, consequently, never known with certainty. By implication, total net farm revenue is uncertain. Accounting for this uncertainty requires specialised MP models.

Models incorporating stochasticity in the coefficients of the objective function have been classified by Hardaker et al. (1991) as risk programming models. Ordinarily in LP formulations, the parameters c_j, a_{ij}, and b_i (expressions 3.8, 3.9) are assumed to be known with certainty. In risk programming, this assumption is relaxed and subsets of the c_j's, a_{ij}'s and b_i's are treated in probabilistic terms. As a consequence, the outcome from any choice of the decision variable becomes a random variable as it depends on the values taken by the parameters. Thus, if it is assumed that the set of x_j's constitute a farm plan, then the decision involves a choice between the resultant x's for the most desirable probability distribution of net returns or some other measure of well-being (Boisvert and McCarl 1990).

The analysis of risk at the farm level has seen the advancement of many different approaches, a number of which have been described by Anderson et al. (1977), Hardaker et al. (1991) and in several other relevant texts. These models apply different forms of mathematical programming to obtain a risk-efficient set of farm plans or an optimal farm plan for a specified level of some particular measure of risk aversion. These various approaches may be regarded as alternative specifications of the Markowitz portfolio theory. Many of them entail more readily computable linear approaches to accounting for risk.

Most risk programming models tend to focus on the stochasticity of objective function parameters and are the easiest to formulate in an MP context. In other risk programming models it is possible to handle risk by including uncertainty in the technical coefficients and/or the RHS values. Typically, applications that attempt to accommodate stochasticity in all three types of parameters are much more difficult both to formulate and solve and to relate to well-known decision criteria (Boisvert and McCarl 1990).

Stochastic programming (SP) is a generic name applied to mathematical programming approaches proposed to deal with risk in the resource constraints (Anderson et al. 1977). According to Hadley (1962), SP models may be sequential or non-sequential in nature. Sequential models attempt to account for the fact that related decisions are made at different points in time implying that risk is embedded. Decisions made at a later stage may be influenced both by earlier decisions and by stochastic parameters. Generally, sequential problems are not amenable to solution by mathematical programming methods though Anderson et al. (1977) have shown the use of discrete stochastic programming in handling such problems. In non-sequential models, risk is assumed to be non-embedded and all decisions are made at the same point in time. As Anderson et al. (1977) and Hardaker et al. (1991) have observed, the biological nature of agricultural production processes implies that most farm planning problems are largely of the sequential type.

Discrete stochastic programming (Cocks 1968; Rae 1971a,b) formulations approximate a sequential stochastic model and are the more usually applied approach. Such formulations attempt an explicit specification of the likely events and decision options in their proper time and sequence.

Linear risk programming models

With the strong assumption of a linear utility function - implying the decision maker is risk-indifferent - in linear risk programming models, the expected profit equals the expected utility and, consequently, maximisation of expected profit leads to the maximisation of expected utility (Anderson et al. 1977). However, according to Anderson et al., decision makers are typically not indifferent to risk, hence other programming approaches that take account of the decision maker's attitude to risk are necessary. Such models include quadratic risk programming (QRP), which is the more commonly used non-linear risk model, and stochastic programming which may be linear or non-linear.

The most widely used of the linear risk programming models is the MOTAD approach suggested by Hazell (1971). It entails minimising risk which is defined as the absolute deviations from the mean net income (revenue) subject to imposed constraints on expected income and other resources. By re-solving the model for parametric variations in expected income, an expected-minimum-absolute-deviation efficient set is obtained. MOTAD has found wide and varied application in risky decision analysis (e.g., Hazell 1971; Thomson and Hazell 1972; Hazell and Scandizzo 1974; Brink and McCarl 1978; Mapp et al. 1979; Persaud and Mapp 1980; Watts, Held and Helmers 1984). As Hazell (1971) explains, MOTAD is justified theoretically as an approximation to quadratic programming.

Target-MOTAD is an extension of the standard MOTAD model proposed by Tauer (1983). The Target-MOTAD formulation, which, like MOTAD, involves defining risk constraints based on observations across several states of nature, generates expected value-deviation (E,D) -efficient set of solutions for some explicitly specified target level of the objective function. As demonstrated by Tauer (1983), the optimal solutions are second-degree stochastically dominant and so are stochastically efficient solutions for risk-averse decision makers following the SEU construct. Watts, Held and Helmers (1984) in their comparison of MOTAD and Target-MOTAD conclude that the latter approach provides a more appropriate framework for risk analysis in agricultural production. Both methods however, generate solutions which are only SSD, not SDRF.

The mean-Gini programming (M-G) approach proposed by Yitzhaki (1982) is another risk programming method that combines the advantages of second-degree stochastic efficiency analysis and those of mean-variance analysis without the limitations of either approach. Okunev and Dillon (1988) have illustrated the use of the mean-Gini formulation in farm planning. According to Hardaker et al. (1991), because mean-Gini efficient sets are always SSD, the programming approach is superior to QRP and MOTAD. However, the mean-Gini approach could be computationally cumbersome and results only in SSD portfolios, not in efficient strategies for a precisely defined class of utility functions or absolute risk aversion interval (Buccola and Subaei 1984).

Quadratic risk programming

Quadratic risk programming is a method of risk programming that has been widely applied in whole farm planning since it was first developed by Freund (1956). A QRP formulation can be used to generate an efficient set of solutions in expected value-variance space which are SSD only with the restrictive assumption either that the decision maker's utility function is quadratic or that the distribution of net income is normal (Hanoch and Levy 1970). The QRP formulation, which usually minimises the variance for uncertain payoffs, may also be employed to maximise expected utility by assuming a negative exponential utility function and also that total net revenue is normally distributed (Freund 1956). A key component of the QRP formulation is the variance-covariance matrix. As noted by Markowitz (1959), if enterprise diversification is to be an efficient hedge against production risk, covariances assume major importance. Activity combinations having negatively covariate gross margins will usually result in a less variable aggregate return than the return from more specialised strategies (Hazell and Norton 1986).

Although QRP has been more commonly applied in the area of investment portfolio analysis, the approach has also seen wide application in risky decision analysis in agricultural production since its application in the area was demonstrated by Freund (1956). However, the assumptions underlying the approach - quadratic utility function and normally distributed net returns - have remained contentious (Rudd 1981; Moriarty et al. 1981; Ritchken 1985; Lambert and McCarl 1985; Patten et al. 1988).

Utility-efficient programming

Utility-efficient programming (UEP) risk programming formulation proposed by Patten, Hardaker and Pannell (1988) is a variant of discrete stochastic programming (DSP) that can be applied to the case where uncertainty is confined to the activity returns. The approach, which is an extension of the Lambert and McCarl (1985) approach, arrives at utility efficient, SDRF portfolios without the need for any restrictive assumptions that have been the subject of controversy in other risk programming techniques such as QRP.

In decision theory, the maximisation of expected utility has been noted by Dillon and Anderson (1990, p. 117) as being 'normatively coherent and logical as a basis for risky choice'. The Lambert and McCarl (1985) proposed direct expected utility maximising non-linear program (DEMP) maintains consistency with the traditional basis of risky decision analysis - expected utility theory - and is free of some of the limitations of risk analysis based on mean-variance analysis. Their formulation may be summarised as follows:

$$\text{maximise} \quad E(U) = p' \, U(z) \qquad [3.11]$$

subject to

$$Ax \le b$$
$$Cx - Iz = uf$$

and $\quad x \ge 0$

where $U(.)$ = a monotonic, concave utility function;
p = vector of state probabilities;
z = vector of activity net revenues per unit;
A = matrix of technical coefficients;
x = vector of activity levels;
b = vector of resource stocks;
C = matrix of activity net revenues;
I = an identity matrix;
u = vector of ones; and
f = fixed costs.

The use of a monotonic and concave utility function means that such non-linear algorithms as MINOS (Murtagh and Sanders 1977) can find a global optimum. The Duloy and Norton (1975) method of linear segmentation can also be used to obtain solutions to the formulation.

By reformulating the Lambert-McCarl DEMP for parametric objective programming, Patten et al. (1988) proposed an approach they termed utility-efficient programming (UEP). Their formulation enables the generation of risk-efficient plans with less than complete information about decision-maker preferences. The UEP formulation leads to 'utility-efficient' farm plans as the parameter, λ, is varied. By noting the optimal solution for each change of basis corresponding to a particular value of λ, the full set of risk-efficient solutions can be derived by interpolation. This set represents the efficient plan at every level of risk aversion in the selected range. No plan outside the generated utility-efficient set is preferred by the decision maker whose preferences have been represented.

Though Patten et al. indicated that the UEP formulation is amenable to the use of different types of utility functions, they emphasise the 'sumex' separable function not only because of its desirable property of decreasing absolute risk aversion but also the ease with which this functional form may be solved by linear segmentation. Hardaker et al. (1991) have demonstrated that the use of a non-separable negative exponential utility function of parametric form

$$U = \exp\,[-\{1-\lambda)r_1 + \lambda r_2\}z_k]\,, \qquad 0 \leq \lambda \geq 1,\ \text{parametric} \qquad [3.12]$$

produced similar results to the sumex formulation. In the above formulation, r_1 and r_2 are the respective upper and lower bounds of the coefficient of absolute risk aversion, r_a; z_k is the farm net revenue for the k*th* state and λ is a non-negative variable parameter which may be interpreted as a measure of risk aversion.

Ogisi, Hardaker and Torkamani (1994) have demonstrated that the utility-efficient programming formulation using a negative exponential utility function produces risk-efficient farm plans which are SDRF. The implied conclusion drawn is that with UEP, the functional form of the utility function used in the formulation is unimportant, in agreement with Meyer (1977a, b) with respect to SDRF. The mathematical relationship between the use of SDRF as an evaluative criterion and UEP remains to be proven, however.

In the light of the hitherto noted advantages of the UEP formulation and its consistency with both the SEU hypothesis and the notions of stochastic efficiency, the approach has been adopted for use in this work.

3.6 Concluding remarks

It has been argued in this chapter that the SEU hypothesis provides a relevant basis for the analysis of the uncertainties of decision making in agricultural production, such as the adoption of a new crop like Linola. The adoption of this criterion implies that the analysis should necessarily be based on the decision makers' preferences for risky outcomes, as indicated by their utility functions, and on their beliefs about the chances of occurrence of those outcomes, encoded through subjective probabilities.

Because of the practical difficulties that accompany attempts at eliciting individual utility functions with confidence, methods of stochastic efficiency have been developed and are judged to be relevant for this study. In particular, SDRF appears to be an appropriate criterion since the range of strategies in the efficient set can be limited by imposing plausible limits on the value of the absolute risk aversion coefficient.

Because Linola needs to be evaluated in a whole-farm context, mathematical programming is considered to be the most appropriate form of model for this study. In particular, the approach of utility-efficient programming combines the advantages of constrained optimisation in a whole-farm context with the concept of SDRF. This method has therefore been adopted for the analysis that follows.

4. Data Collection, Collation and Analysis

'Things are not always what they seem'

- Anon

4.1 Introduction

Some of the theoretical concepts that form the basis of the modelling of case farms in the study area have been discussed in previous chapters. Empirical application of the outlined approaches requires comprehensive data sets from the farms under consideration and the general locality in which the farming operations take place. The collection, collation and preliminary analysis of these data are described in this chapter. The types of data collected are reported and the rationale established for the approaches taken for the computations of some of the technical coefficients.

Data used in this work were obtained from both primary and secondary sources. The data for each study farm was obtained via questionnaires designed to be easily understood by the farmers. The first farm visits took place early in 1994 and a second follow-up visit for the purpose of verifying the respective farm models and to cross-check some of the applied data took place early in 1995, about a year later.

Certain farm-specific data could not be obtained by the author due to a lack of research resources. For these data, district averages were obtained from the Victorian Department of Agriculture (VDA) and the Victorian Farmers Federation (VFF) and were assumed to be applicable to all the case farms used in this study. This assumption was considered reasonable since the case farms are located in the same agroclimatic zone.

Crop yields and prices used in each of the models were unique to each farm as they were based on farmer expectations obtained through the scaling procedure described later in Section 4.5. In essence, detrended yield and price data used for each farm model were subjectively adjusted to reflect the expectations of each farmer (as explained in Section 4.5 below). It was assumed that the five case farms in this study cultivated similar crop varieties as recommended for the district by the VDA (Carter 1991).

All the necessary plant and field machinery are assumed available on each of the case farms except for headers which are assumed hired on contract. Excess harvesting capacity in the district has generally reduced the trend towards individual ownership of combines as the cost of maintenance have been thought by farmers to exceed the value of the insurance provided for losses due to untimely harvesting of crops (Wightman, B. 1994, pers. comm.)

The rationalisation of the choice of the case study approach for this work is provided in Section 4.2. Section 4.3 is a description of the study area and the case farms. The sources of primary and secondary data, methods of analysis and the treatment of missing data are discussed in Section 4.4. The discourse in Section 4.5 covers the elicitation of the subjective probabilities of the farmers and others involved in the study. The approach used for the measurement of individual preference intervals is described and rationalised in Section 4.6. Results obtained from the implementation of the preference measurement procedure are also presented.

4.2 Representative versus case study approach

In the whole-farm modelling approach, there are two main options in the type of data that is collected for use in the farm model. These are either the representative farm or the case study farm option. A representative or typical farm, which is not usually an identifiable real farm, is generally formulated to represent both the average or typical situation of farms in the study area. Thus, it is usually constructed to be of median (mean) size and to have the typical relative resource endowments of the group of real farms it is supposed to represent. For this reason, the results obtained for the 'representative' farm will not apply to any specific farm but may be applicable to some group of farms, on average. When the modelling process requires incorporation of individual beliefs and preferences, the average or median individual may be difficult to define. Serious questions exist as to whether a 'typical' farm can effectively reflect the differences in the managerial abilities, tenural arrangements, capital availability, and personal bias and goals of individual farmers. In recognition of the fact that each farm represents a unique case, the case study approach was elected for use in this study.

A case study farm is one that is studied in sufficient detail to understand many of the cause and effect relationships that exist on the farm. It has the advantage of reflecting actual circumstances of a particular farm, not some amalgam of the circumstances of many farms. Conclusions may be extrapolated to the target farm population provided that sufficient information is available about the population in terms of those features revealed by the case study to be important. Barlow, Jayasuriya and Price (1983) have noted that some degree of generalisation for case study farms may be justified if farms are chosen to represent particular production environments. The case study approach allows direct incorporation of decision maker beliefs and preferences in the models developed to mirror the production decisions taken on the specified farm.

In the current study, Linola is being grown on a trial basis by farmers in the Barwon district. Since farmer beliefs and preferences influence their decision to adopt new production techniques, these may be easily incorporated in the models which become unique for the particular case farms. This further validated use of the case study approach in this study.

4.3 Study location and choice of case farms

The case study farms are located in the Barwon Statistical District (hereafter called Barwon) of Victoria, all within a 120 km radius of the Shire's main city of Geelong. The location of the Barwon statistical division is shown in Figure 4.1.

Located in the Western District, Barwon comprises fourteen Statistical Local Areas (SLA) including the shires of Colac, Winchelsea, Leigh and Barrabool, where the farms used in this study are located. These shires have a combined population of about 22 620 (ABS 1992).

The climate in the area is mainly humid, temperate. Most of the area has mean annual rainfall exceeding 600 mm (Bureau of Meteorology, 1995). A summary of the average annual distribution of rainfall in Victoria is shown in Figure 4.2. The major topographical determinant of the Victorian climate is the Great Dividing Range which acts as a barrier to the moist south-east and south-west winds and this, combined with its coastal proximity, causes the south of the State to receive more rain than the north (ABS 1994). The expanse of ocean that borders south Victoria exerts a moderating influence on the winter climate between the months of May to August and, in consequence, snowfalls are rare on areas under an elevation of 600 m. Generally, summery temperatures occur between the months of November to February. The rainy period is mainly between March and August, though rains may occur year-round.

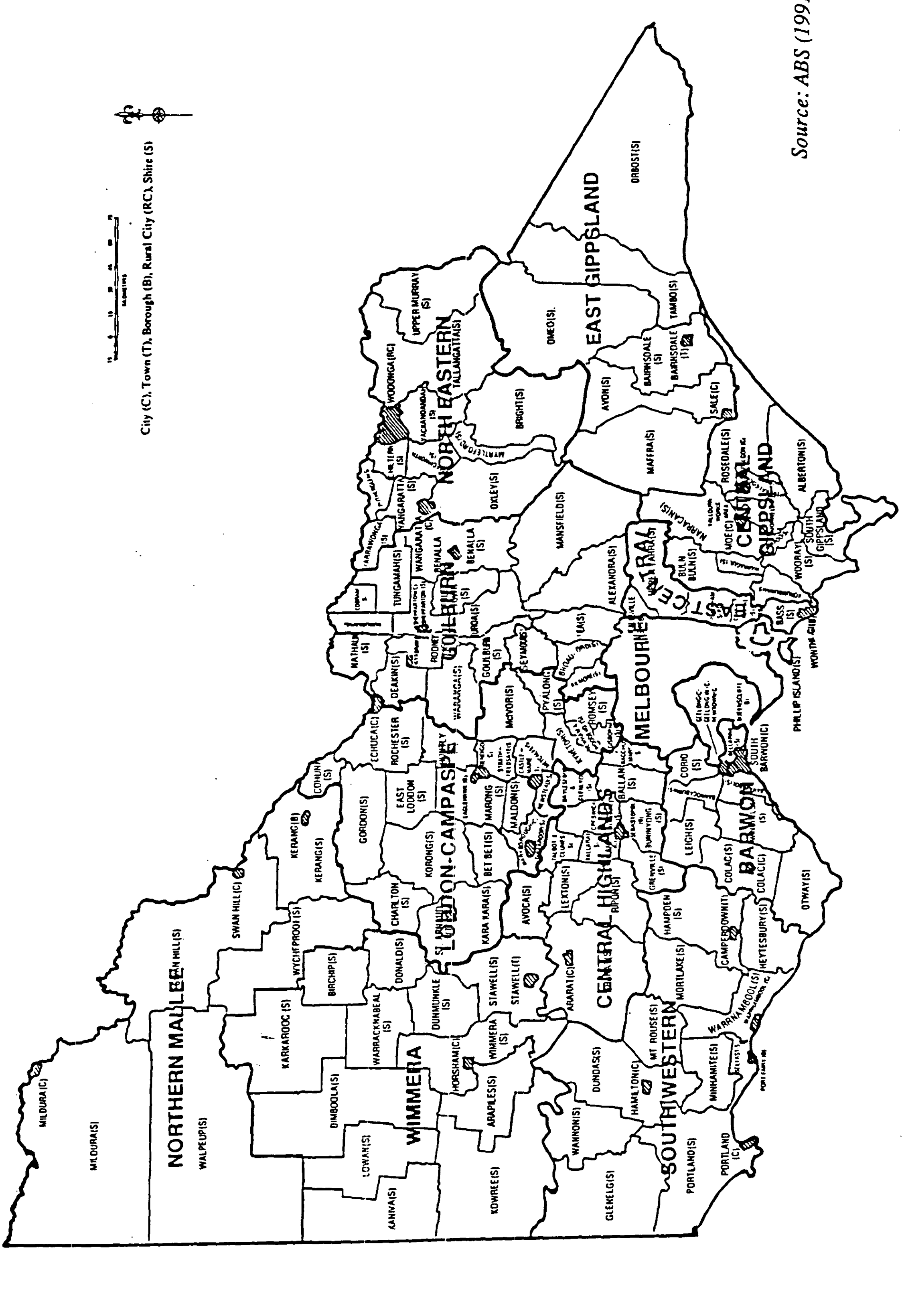
The soils are mainly basaltic ranging from yellow and brown podzolic and solodic (Walker et al. 1983) to alluvial soils. The top soil is usually shallow, 10-30 cm, overlying heavy clay subsoil. Most of the soils are generally considered good though they may be acidic and deficient in nitrogen, copper, sulphur and phosphates and prone to waterlogging as a result of the thick, plastic clayey subsoils with low permeability (Wightman, B. 1994, pers. comm.).

Land use in the district varies widely from grazing in the drier inland range-lands to cash cropping in the more humid coastal locations to industrial and urban uses in the major cities. The predominant agricultural activity in Barwon, however, is crop production with a significant level of combined crop and livestock production as shown in Table 4.1.

According to the 1994 ABS survey, the Victorian average farm/establishment size was 349 ha (down from 393 ha the previous year) compared to the Barwon average of 239 ha (down from 286 ha in 1993).

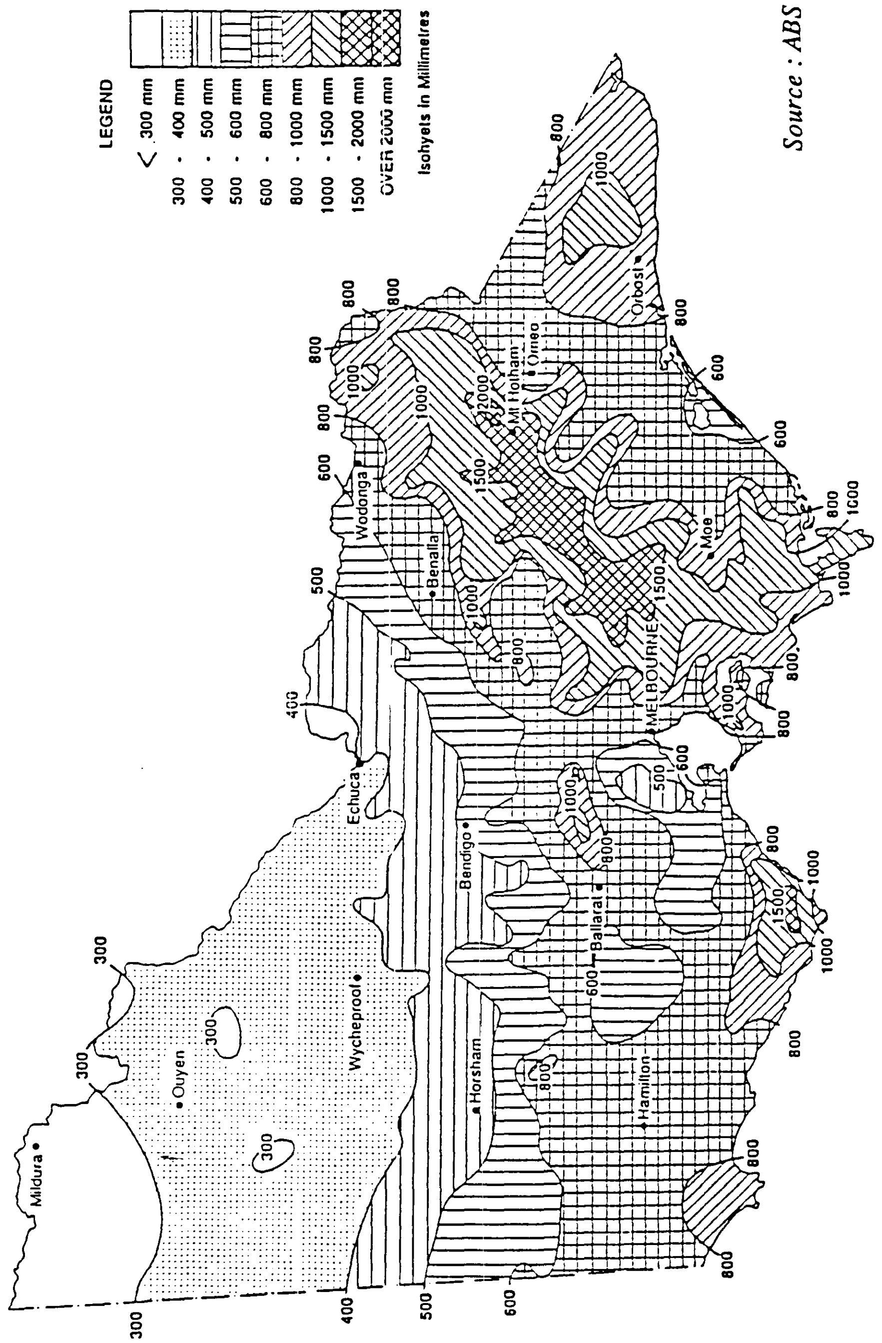
The total sheep and lamb population in the district was reported to be 1.3 million. Cattle numbered about 225 000 and pigs just under 7000 in 1993/94 (ABS 1995).

The general pattern of land usage in Barwon is provided in Table 4.2. It can be observed that, although wheat is the main crop grown in Victoria (33.8 per cent of total land use), in Barwon, barley is the major crop, accounting for about 35 per cent of total cropped land. The area sown to wheat in Victoria (Figure 4.3) declined by over 50 per cent in the six-year period between 1986/87 (1.36 million ha) to 1991/92 (0.6 million ha, ABS 1994) and then increased again between 1993 and 1995. In contrast, the area sown to barley has shown a rising trend over the same period from little over 440 000 ha to 900 000 ha. Oilseeds account for close to 9 per cent of arable land usage in the Barwon



Source: ABS (1991a)

Figure 4.1 : Statistical divisions of Victoria



Source : ABS (1994a)

Figure 4.2 : Annual rainfall distribution - Victoria

district with linseed constituting about 4 per cent of the total. Over 95 per cent of the total Victorian production of linseed is grown in the Barwon area, making it an area with reasonable potential for the adoption of Linola given the similar agronomic requirements of both crops as previously discussed in Chapter 2.

Rotation practices have become popular with the increasing awareness by farmers of the effects of intensive cropping practices on the chemical properties, physical structure and future productivity of the soils. Also, when crops such as oilseeds are introduced into crop rotations, the build-up of soil-borne diseases is interrupted, hence these crops are commonly described as 'disease break' crops.

There has been a general transition away from using aggressive soil tillage implements such as the mould board plough to the disc, chisel and scarifier ploughs, and herbicides are being substituted for mechanical weed control (Bluett, C., 1994, pers. comm.). In recognition of the fact that their production systems must be both sustainable and profitable, various methods of conservation farming are becoming popular in the area. Direct drilling (zero-tillage) is also gaining in popularity despite claimed benefits of deep tillage (Ghadim et al. 1991). Although no known studies of the influence of zero-tillage on crop performance have been reported for the Barwon area, studies in northern New South Wales have indicated significant yield increases (Martin and Felton 1985; Collett 1984) due to improved soil structure and more active earthworm populations.

The choice of farms used as case studies was not governed by any statistical considerations but by opportunism in that relatively few farmers have taken up growing Linola, which is the focus of this work. The only consideration given to the selection of the study farms was that each had grown linseed over at least four seasons, not necessarily successively, at some stage previously and had grown Linola on a trial basis for at least two seasons. A list of the only eight farms that had grown the crop on a trial basis in the Barwon District of Victoria was obtained from the Victorian Department of Agriculture and Seedex (CSIRO's commercial arm) and all were originally interviewed but three were dropped because of recurrent inconsistencies in their responses to the section of the questionnaire on preference interval estimation (described later in this chapter) and also because they had grown the crop for only the previous growing season. The statistical divisions of Victoria, including the study area of Barwon, are as shown in Figure 4.1.

4.3.1 Case farm one

Case farm number one is located in the shire of Winchelsea and is family-operated by two brothers, one full-time and the other part-time. The full-time farm operator, who is under 40 years old and sees farming as both a way of life and a business, attained a year 11 education before joining the family business of farming. The farmer has a wife and two children, both of whom are under ten years old.

The total farm area is some 1300 ha of which 900 ha is arable. The non-arable 400 ha is under natural pasture. Of the 900 ha of arable land, 520 ha is cropped and the remaining 380 ha sown to improved pasture.

The topography is mainly undulating land varying from light friable loam to heavy clay soils that sometimes require the application of gypsum to improve friability and the stability of the clays.

The main crops grown include wheat, triticale, barley, linseed, Linola, and clover which is used for hay. Wethers are run for wool and first-cross lambs produced for the fat-lamb market. The total stock of sheep is usually kept at about 6500.

The farmer also keeps about 520 000 broilers on an 'all-inputs-supplied' contract basis in which case only the farmers' labour and management are required inputs into the enterprise.

According to the farmer, the level of the cropping enterprises varies each year depending on price expectations based on the information about the previous season. At times, the farmer places limits other than rotational constraints on the production of certain crops because of the risk of crop failure.

Two permanent farm hands are employed with casual labour employed as needed during the year, particularly at harvest and shearing time. Some off-farm contract work is done for other farmers (land preparation, harvesting, hay baling) and the shire (highway grass verge mowing). A summary of some of the performance indicators for this farm is presented in Appendix Table A10.1.

Table 4.1 : Agricultural land use in Victoria, 1993/94

Enterprise	Sown area	Proportion of total area	Proportion of cropped area
	ha	ha	%
Cereals:	1 652 000	12.70	71.30
Wheat	783 895	6.02	33.83
Barley	639 493	4.91	27.51
Oats	185 840	1.43	8.02
Triticale	32 000	0.25	1.38
Rye	13 000	0.10	0.56
Oilseeds:	(66 000)	(0.51)	(2.85)
Canola (rapeseed)	29 050	0.22	1.25
Linseed	1 290	0.01	0.06
Safflower	29 710	0.23	1.28
Sunflower	1 390	0.01	0.07
Legumes	421 000	3.23	18.17
Other crops	153 958	1.18	6.64
Total cropped area	2 317 000	17.80	100.00
Pasture - native	2 124 000	16.32	
Pasture - sown	6 122 000	47.03	
Other usage[a]	2 454 000	18.85	
Total land area	13 017 000	100.00	

[a] Includes vegetables, fruits and nuts, and grapes.

Source: ABS (1995).

Table 4.2 : Average land use in Barwon district, Victoria, 1993/94

Enterprise	Sown area	Proportion of total area	Proportion of cropped area
	ha	ha	%
Cereals:	(21 373)	(4.65)	(64.58)
Wheat	2 613	0.57	7.89
Barley	11 636	2.53	35.16
Triticale	2 305	0.50	6.96
Oats	4 766	1.04	14.40
Other[a]	53	0.01	0.16
Legumes	1 595	0.35	4.82
Oilseeds:	(2 869)	(0.62)	(8.67)
Linseed[b]	1 273	0.28	3.85
Canola	1 083	0.24	3.27
Sunflower	513	0.10	1.55
Other crops	7 258	1.58	21.93
Total cropped area	33 095	7.20	100.00
Pasture - native	81 000	17.62	
Pasture - sown	270 753	58.89	
Other usage[c]	74 900	16.29	
Total land area	459 748	100.00	

[a] Mainly ryegrass seed.

[b] Including Linola.

[c] Includes vegetables, fruits and nuts, and grapes.

Source: ABS (1995).

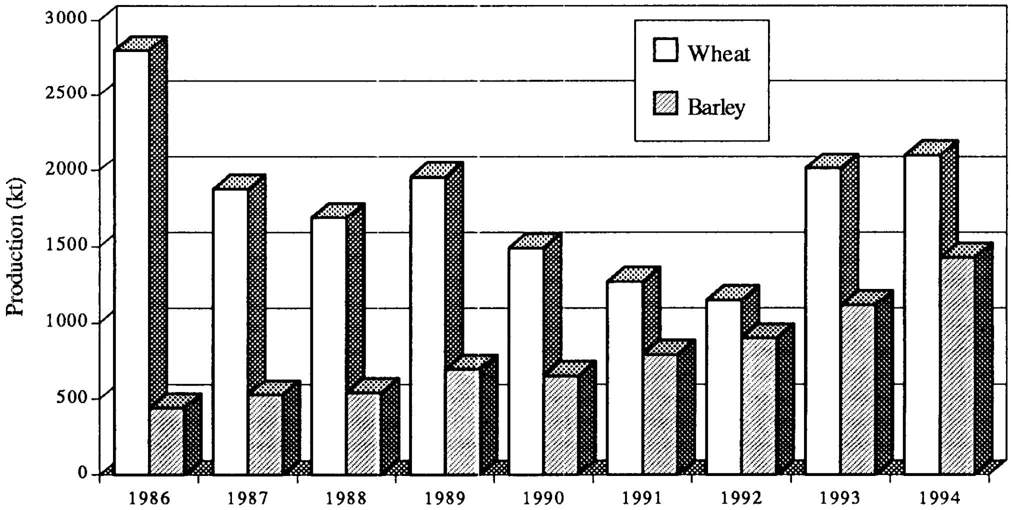


Figure 4.3 : Trends in the production of wheat and barley in Victoria, 1986/87 to 1994/95

4.3.2 Case farm two

Case farm number two is a family-operated farm of 750 ha located in the shire of Leigh, with an owner-estimated walk-in, walk-out value of $1.2 million. Of the total arable area of 500 ha, 227 ha is cropped and 186 ha sown to improved pasture. The operator is a 43-year-old graduate diploma holder who inherited the farm from his father 20 years ago.

The topography is mainly flat land ranging from basaltic loam to clay. There are scattered areas of rocky outcrops suited to little but running sheep.

The main crops grown, mainly by direct drilling, include wheat, barley, sunflower, linseed, grain oats and recently, Linola. All crops are sold at harvest and may be contracted mid-season. Some of the oats may be fed to stock if and when necessary. Sown pasture, which is cut for hay, is mainly clover, sometimes mixed with phalaris. Chemical application is usually done by contract and up to 60 per cent of crop harvest (100 per cent for sunflower) is also usually done by contract.

Wethers are run for wool based on a self-replacing Merino flock and cross-bred lambs are produced for the fat lamb market. At the time of the last visit to the property in April 1995, there were 3200 sheep on the farm.

One permanent farm hand is employed on the farm. Main casual labour employment is for shearing in September/October and April/May. The main performance indicators for case farm two are provided in Appendix Table A10.2.

4.3.3 Case farm three

Case farm number three is a 960 ha farm located in the shire of Leigh. It is owner-operated full time and comprises 787 ha of arable land and 173 ha of non-arable land planted to natural pasture. The 37-year old operator, who inherited the property about 21 years ago, was educated to year 12 and has a wife and three children who sometimes help with farm work. The property, currently valued at over $2 million, has been in the family for over a hundred years. The only change through the years has been the acquisition of more land.

The soil on the farm ranges from sandy loam to heavy clay which gets waterlogged in very wet years.

The favoured crops include wheat, barley, triticale, Canola, lupins, field peas, linseed and, recently, Linola. However, the operator indicated that crop rotations are not set and may change from year to year depending on price expectations. Linola and linseed are grown because they tolerate water-logged soils or 'wet feet'. Sown pasture consists mainly of sub- and white clover.

Low-maintenance wethers are bought in annually for wool production and sold for meat. No self-replacing flock is maintained. The decision to purchase wethers each year is based on the expected change-over price differential.

A part-time farm hand is employed, for four days of each week.

Wheat is usually sold privately (i.e., not through the Wheat Board) but barley is sold directly to the Barley Board. Oilseeds are sold mid-season or at harvest to crushers, but linseed may be sold as bird seed to agents. Sometimes oilseeds may be grown on fixed-tonnage, fixed-price contracts. General performance indicators for this property are given in Appendix Table A10.3.

4.3.4 Case farm four

The property identified as case farm number four is an owner-operated farm of 862 ha (650 ha of which is leased) located in the shire of Barrabool. Of the 862 ha comprising the farm, 800 ha is arable and 62 ha non-arable. The non-arable area is planted to natural pasture. About 72 per cent of the arable area is sown to pasture (mainly lucerne which is cut for hay) leaving 220 ha for cropping.

The soils on the farm vary from light sandy soil to medium to heavy loam. Rainfall is close to the district average but winters are wet in normal years.

The property owner, aged 45, attained a year 11 (matriculation) education and has a wife and three children. The wife is actively involved in the farming operation as book-keeper and all three children help out on the farm when they are able to.

The crops of choice grown on the farm include Canola, linseed, Linola, barley (feed or malting), field peas, turnips and canary seed. Linola was not grown in the 1994/95 season because of the withdrawal of the growing contract by Seedex. Turnips are mainly fed to sheep.

Land preparation is moving towards minimum tillage options. Some crops such as barley and turnips are direct drilled. For the heavier soils some level of conventional cultivation still takes place, viz. disc ploughing, scarifying and harrowing.

Both cattle and sheep are run on the farm. Sheep activities include merino breeding, wethers and fat lamb production based on 'comeback' ewes crossed to Border Leicester or Dorset Horn rams. The Sheep flock is self-replacing. As at April 1995, the farm had 4500 sheep including 1650 breeding ewes. Beef cattle enterprises include vealer production using mainly Herefords, Angus, Limousin, Belgian Blue and crosses to maintain a 200-cow breeding herd. Sometimes replacement heifers are bought in. According to the operator, the difference in the price of vealers and fatteners is not sufficient to warrant the extra effort and time of keeping fatteners except on the odd occasion. Main performance indicators for the farm are provided in Appendix Table A10.4.

Off-farm activity includes contract haymaking for neighbours up to a maximum of 200 h annually. Verge mowing for the shire council may sometimes be an option but this is not a regular activity.

Crop sales are mainly after harvest to the various pertinent commodity boards. Barley is sold to the Barley Board and linseed to Southern Grains. However, Canola and canary seed may be forward contracted on the basis of fixed tonnage for a fixed price. Sheep and cattle are sold either through the saleyards or directly on the property through the computer-aided livestock marketing (CALM) system. Sometimes, fat lambs may be forward contracted for the export market.

4.3.5 Case farm five

Case farm number five is located in Colac shire. At 1800 ha total area, currently valued at $3.2 million, the farm is bigger than the district average and is fully owned by the operator. The 36-year old operator's highest educational achievement is a farm management diploma. The family size is four with two children who are under ten years old.

Rainfall average on the property between 1992 and 1994 was about 575 mm.

The topography is mostly flat to slightly undulating land with soil types ranging from alluvium silt to light clay. Of the 1800 ha of farm land, only 206 ha is arable. Of the remaining 1594 ha, 74 ha is unusable fenland and the rest is under natural pasture. Ninety-six ha of the arable land is sown to improved pasture.

The crops of choice on this farm include wheat, barley, forage oats, triticale, lucerne, Canola and Linola. Linola was not grown in the 1994/95 season because of the withdrawal of the growing contract by Seedex. Sown pasture is mainly medic, sub-clover and lucerne. Lucerne is usually cut twice - first cut for silage and second cut for hay.

Sheep and cattle are raised as a self-replacing flock and herd respectively. Wethers are raised for wool and breeding ewes to maintain the flock size. Cattle activities include weaner production, steers, heifers and vealers from a breeding herd of 150 cows. The average stocking rate on the property is about 9.8 DSE/ha.

Cereals are direct drilled but oilseeds are more traditionally sown, i.e., land is ploughed (disc plough) and scarified.

The farmer employs one full-time permanent farm hand and casual labour is employed as required through the year, especially at harvest and shearing times. About 200 h each year is expended on off-farm work such as hay-baling. Canola windrowing is usually contracted.

Crop harvesting is usually contracted and crops are normally sold on the open market. Most of the harvested barley is sold to local dairy farmers, and ewes and wethers are sold for export on the property. Wool is generally sold at auctions or to brokers. Cattle are sold on the property or through the saleyard at Colac. Fatteners are mainly sold for export. The main performance indicators for case farm five are as provided in Appendix Table A10.5.

4.4 Data collection and analysis

Most of the data used in this work were collected between March 1994 and April 1995 from the case-study farms previously described. Prior to visiting the case-study farms, the author conducted interviews with various VDA and VFF staff in Geelong, Colac and Ballarat to become familiar with the area.

Care was exercised in the collection and collation of the large volume of data required for the whole-farm modelling approach adopted for this study. The data requirements were farm-specific and general, as further explained below.

Farm-specific data on the resource base, technical coefficients and production/personal objectives for each case study farm were obtained by administering a questionnaire (Appendix A1) designed to be simple and comprehensible to the farmers. The questionnaire, which had been pre-tested on three farmers in the New England area, was personally administered by the author in all cases. The sessions which averaged three hours, were usually broken into segments to avoid boredom. The respondent farm operators were generally cooperative and helpful during the interviews which were also recorded on tape. As a rule, data were extracted from the questionnaire onto a laptop computer on the day of the interview.

Information was obtained for both crop and livestock activities. To enable subjective scaling of the data as later described, information was obtained on farmer price and yield expectations based on the triangular distribution. Information was also obtained on farmer attitude toward and perception of risk. As a consequence, probability distributions for crop yields and prices used in each of the models were unique to each farm as they reflect the subjective expectations of each farmer. Given the Fischer (1985) and Roling (1988) propositions that educational achievement affects the manner in which information concerning a new technique is processed, data were also collected on the amount of schooling received by each of the respondents. All farmers had had at least 11 years of formal schooling and been in agricultural production for at least 10 years. The average age of the respondents was 40.2 years.

The general sensitivity of the issue of taxes informed the decision of the author to use pre-tax farm income as the modelling basis. Information was not collected on family assets outside the farm such as shares, bonds and short- or long-term bank deposits. As a consequence, it was assumed that it is the changing wealth status of the producer as per farm returns that influences the production decisions made on each of the case farms.

Data were also collected about sources and uses of credit for each farm. The main sources of credit were the various financial institutions including credit unions and savings/trading banks. Other sources of credit include pastoral and non-pastoral finance companies, assurance societies as well as government sources. The types of credit available include negotiable leases, fixed-term loans which are usually mortgagee-secured, bank overdrafts and government assistance. It was found that the five farmers studied in this work generally imposed limits on their borrowing on the basis of the estimated walk-in, walk-out values of their properties. While each agreed that these limits could be exceeded in dire times, they indicated that such recourse had not been necessary in the last 5-7 years despite the downturn in the rural economy. Too, information was obtained about carry-over funds from the end of one season to the start of the next.

Information was collected on the availability and use of labour on each farm. On the basis of information obtained from the individual farmers, effective available labour was computed as the total labour available (operator, family, permanent employed, part-time) less vacations, periods of ill health and miscellaneous family time allowance. For the operator, periods of field day attendances and other miscellaneous extra-farm activitites were also deducted to arrive at the total available labour. An eight-hour working day over a six-day week was assumed.

Household labour available for farm activities is both a function of non-farm committments, including leisure and schooling, and the composition of each household. The mean household size was 4.4. Since there are other competing uses of family 'labour' such as schooling, off-farm work and leisure, the use of family time was assigned to the periods when labour was in short supply - planting and harvest. The amount of family labour, apart from operator labour, available for farm work was computed taking into consideration the family size, age distribution and competing demands for family time outside the farm. Children under 10 years were assumed to provide no labour towards farm operations. Also wives who worked full-time off-farm were assumed to provide no on-farm labour. No attempt has been made to treat family labour not used for farm activity as representing forgone earnings or expenditure (Becker 1965).

An inventory of physical assets on each of the case farms was obtained via the questionnaires, as were estimates of maintenance costs.

Farm-specific data were cross checked for accuracy and correctness during the follow-up visit about a year after the first visit to the farms. On this occasion, a reduced form of the previous questionnaire was administered and the responses checked with the previous ones for consistency. Generally, the respondents were consistent in their replies about technical data. The few inconsistent responses were clarified in consultation with the farmers. Mainly, these were a result of apparent memory lapses that were sorted out on further discussion with the respondent.

General and specific data on Linola were mainly obtained from CSIRO and the Victorian Department of Agriculture (VDA), Geelong. A CSIRO researcher and an extension officer with the VDA, Ballarat, were interviewed to obtain information about their perceptions concerning the new technology. These perceptions were incorporated in the models for each case farm. Time series data on prices, yields and costs of the major farm inputs including fertilisers and chemicals were mainly obtained from ABS, ABARE, VDA and the Victorian Farmers Federation (VFF) publications between 1970 and 1994 and transformed into subjectively adjusted values in the manner described later in Section 4.5. It is recognised that the aggregation of yields across farms in a district may tend to reduce variability due to imperfect correlations, but these problems are not easily overcome. Annual mean rainfall and mean annual ambient temperature data for the district were obtained from the Bureau of Meteorology, Melbourne. Data on feed and energy requirements for livestock, sheep and cattle, in Livestock Months (LSM), were obtained mainly from Rickards and Passmore (1977). Forage production estimates in LSMs were also obtained from Rickards and Passmore. Prices of the various classes of livestock were obtained from the farmers and cross-checked with those obtained from the Colac and Geelong saleyards in the years for which this was an option.

Since no data were available to enable the researcher to assign probabilities to the years for which historical activity net revenue data were obtained recourse was had to the 'principle of insufficient reason' in assuming that the subjectively scaled activity revenue sets based on the twenty-five production years (1970-1994) of data were equally likely states of nature.

Preliminary analysis of the data was done using EXCEL and MINITAB which are both amenable to the handling of a large volume of data. The database was set up following the approach suggested by Friedrich (1977). Most data fields within the worksheets were cross linked by formulae to minimise data entry and re-entry errors. Careful 'eyeballing' was carried out to ascertain the integrity and logical consistency of all analysed data.

Detrending (linear) of historical price and yield data prior to their correction was carried out using MINITAB following Karmel and Polasek (1977). Detrending was necesssary to eliminate the effect of technological change and inflation.

Individual farm gross margin budgets for crop and livestock activities (Appendices11-15) were computed and analysed on EXCEL spreadsheets using the subjectively adjusted data (Appendices 3-8) for each farm. As noted earlier in Section 4.3, direct drilling is gaining in popularity in the district. In consequence, the crop activity budgets were constructed on the basis of reduced land preparation. Although all the case study farmers owned tractors and land preparation equipment, harvesting was mostly contracted. This was accordingly reflected in the activity budgets. With livestock activities, the only contracted work included in the activity budgets was the shearing of sheep.

4.4.1 Missing data

Being a new crop, no historical data were available for Linola. Relevant yield and technical coefficient data for the crop were generated based on linseed data given their agronomic and biological similarities. As indicated by CSIRO (1994), Linola varieties, *Wallaga* and *Eyre,* have yields 5-10 percent better than their parent linseed cultivars. Consequently, for each data point, relevant historical linseed yield data were inflated by 7.5 per cent for the years between 1970 and 1990. This was also considered a way around the problem of using time series that may be low for a crop due to the inexperience of the growers with the crop.

Linola price data were obtained by assuming a positive unitary correlation between Canola and Linola prices. This assumption is based on the results presented in Table 2.7. As discussed in Chapter 2, the demand for most oilseeds is a derived demand driven by the demand for the various oils. Linola oil is identical in composition to sunflower oil for which it would be a potentially perfect substitute. From Table 2.7, the highest price correlation is between Canola and sunflower prices. Given the apparent high substitutability of Linola and sunflower oils, it was assumed that the same level of correlation would exist between Canola and Linola oil prices. A correlation of +0.9 was thought to be close enough to assume unitary correlation between Linola and Canola prices between 1970 and 1990.

Data for triticale were not available prior to 1975 as the crop was not commercially grown in Australia before that year. To obtain yield data for the years between 1970-74, an ordinary least squares regression was run using yield data (3-year moving average) between 1975-94 with precipitation (district 3-year moving average) and mean ambient air temperature (3-year moving average) for the same period, as independent variables (Johnson and Finley 1963; Shaw 1964; Chmielewski 1995). As previously indicated, mean annual precipitation and mean annual temperature data were obtained from the Bureau of Meteorology. The resulting relationship was then used to extrapolate triticale yields for 1970-74. The estimated relationship is given by:

$$TY = 0.299 + 0.0037P - 0.2297A \qquad (SE = 0.1687, R^2 = 0.8497) \qquad [4.1]$$

where TY is the predicted triticale yield between 1970 and 1974, P is the mean annual precipitation and A is the mean annual temperature.

Relevant price data for 1970-74 were similarly obtained by regressing triticale price on wheat and barley prices. The estimated OLS price relationship is given by:

$$TP = 21.01 + 0.3308WP + 0.3957BP \qquad (SE = 8.0479, R^2 = 0.8736) \qquad [4.2]$$

where TP is the predicted price per tonne of triticale for the years 1970-1974, WP is the price per tonne of wheat and BP is the price of barley per tonne.

In light of the time and financial limitations of the author which restricted the time spent on each farm, it was not possible to obtain all the necessary technical coefficients from each of the farms. In these instances, the information was obtained from the VDA extension officer who has dealt with these farmers for several years and also maintains trial plots for varying crops on the farms. His estimates were therefore considered reliable for the purposes of this work. On occasion, recourse was made by the author to 'informed subjective guestimates' for technical coefficients after consultation with the farmers and VDA extension workers.

4.5 Elicitation and assessment of subjective probabilities

For the elicitation of individual subjective probabilities for yields and prices, the triangular distribution was used. The farmers were simply requested to indicate the lowest, mode or most likely and the highest values for each uncertain quantity. As noted by Anderson et al. (1977), the cumulative distribution function (CDF) of the triangular distribution is of the form:

$$F(x) = (x\text{-}a)^2/[(b\text{-}a)(m\text{-}a)] \qquad \text{for } a \leq x \leq m \qquad [4.3]$$

and

$$F(x) = 1\text{-}(b\text{-}x)^2/(b\text{-}a)(b\text{-}m) \qquad \text{for } m \leq x \leq b \qquad [4.4]$$

where x = value of risky prospect;
a = lowest possible value of x;
b = the highest possible value of x;
and m = the most likely value (mode) of x.

By equating *F(x)* with a pseudo-random uniform variate, u, over the interval of zero to unity, the expression given by 4.4 can be solved for a corresponding triangular variate, x. i.e.

$$x = a + [u(b\text{-}a)(m\text{-}a)]^{0.5} \qquad \text{for } a \leq x \leq m \qquad [4.5]$$

and

$$x = b - [(1\text{-}u)(b\text{-}a)(b\text{-}m)]^{0.5} \qquad \text{for } m \leq x \leq b \qquad [4.6]$$

where a, b and m are as previously defined.

Crop yields and prices may be expected to be stochastically dependent implying the requirement of their joint distributions. However, as recognised Anderson et al. (1977), the elicitation of the multivariate distribution of crop yields and prices from farmers is intrinsically difficult. Consequently, recourse had to be made to the use of subjectively adjusted historical data following Lin, Dean and Moore (1974).

Generally, input-output relationships were based on agronomic, physical and biological data obtained for each farm in so far as that was possible. As earlier mentioned, the time series data on crop yields and prices were obtained from various ABS and ABARE publications and the Victorian Farmers Federation year books for the period, 1970-1994. To eliminate the effect of technological change and inflation, the data were detrended and then scaled to have similar means and standard deviations as those elicited from the farmers using the triangular distribution. The following relationship was employed in transforming the historical time series data:

$$Y_{sjk} = M_{sj} + [(Y_{djk} - M_{dj})/SD_{dj}]SD_{sj} \qquad [4.7]$$

where Y_{sjk} = subjectively transformed yield or price for crop j in state k;
M_{sj} = mean of subjective distribution for crop j;
Y_{djk} = detrended data crop j and state k;
M_{dj} = mean of detrended data for crop j;
SD_{dj} = standard deviation of detrended data for crop j; and
SD_{sj} = standard deviation of the subjectively transformed distribution for crop j.

This adjustment procedure preserves the nature of the correlations and the inherent stochastic dependency of the original historical data. Since no information was available to enable the researcher to assign varying probabilities to the data for the years considered in this work, recourse was made to the 'principle of insufficient reason' (Halter and Dean 1971) in assuming that the 25 production years (1970-1994) of data used in this work were equally likely states of nature after subjective scaling. Examples of the detrended and transformed data series are presented in Appendices 4-8. All initial data analysis and budget computations were done on EXCEL spreadsheets.

4.6 Individual preference measurements

King and Robison (1981a,b) have advanced an operational procedure for eliciting decision maker risk attitudes based on the SDRF criterion developed by Meyer (1975, 1977a,b) as discussed in Chapter 3.

The interval approach to measuring decision maker preferences allows the estimation of the lower and upper bounds of a decision maker's absolute risk aversion function which is a prerequisite for SDRF analysis. Unless otherwise stated, references in this section will be to King and Robison (1981a), a summary of which is presented. According to King and Robison, the approach, '...uses information revealed by a series of choices between carefully selected distributions to establish lower and upper bounds on an individual's absolute risk aversion function'. The procedure is based on the fact that, under certain conditions, choosing between two distributions defined over a relatively narrow range of outcomes divides absolute risk aversion space ($-\infty$ to ∞) over that range into two regions - one region which is consistent with the choice made and the other not. The properties of the two distributions thus define the consistent and inconsistent regions (Meyer 1977a,b). Thus, by providing a decision maker with a series of choices between carefully selected pairs of distributions, it is possible to identify the region in absolute risk aversion space that is consistent with the decision maker's indicated preferences. Each choice made by the decision maker allows narrowing of the absolute risk aversion range. The 'choice-narrowing' process continues until a desired accuracy level is achieved.

The range of absolute risk aversion is determined at four levels of the performance variable, pre-tax net income. By making interval measurements in the region of several outcome levels and linearly interpolating between known values, lower and upper bound risk aversion functions can be constructed over a wider range of outcomes.

Implementation of the interval approach requires:
1) specification of a measurement scale which determines the degree of precision with which preference measurements can be made;
2) generation of sample distributions and identification of the boundary intervals for the paired distributions using a customised computer program;
3) formulation and administration of a questionnaire; and
4) using respondent interval preferences to order selected alternatives.

Following the above steps, the starting point for the procedure was the careful specification of a measurement scale that serves as a set of reference levels of absolute risk aversion on which preference measurement was based. The number of reference levels on the measurement scale depends on the number of comparisons the decision maker will be requested to make. Generally, if N choices are to be made in measuring the absolute risk aversion for a specified output level, the measurement scale should comprise as least 2^N reference levels. If, as in this instance, the decision maker is required to choose between two distributions, then the measurement scale should comprise four absolute risk aversion levels.

The next step is the generation of the sample probability distributions that will serve as the basis for the choices intended to reveal the decision makers' preferences. The pseudo-random distributions are generated using a simulation model (INTID - as listed by King and Robison) for a specific distributional form, e.g. normal, beta and gamma.

King and Robison assume a normal distribution which can be simulated by supplying values for the mean and standard deviation.

The program, INTID, generates a sample of hundreds of sampled values based on indicated parameter values. These sampled values are then grouped into sets of observations or elements considered to be equally likely outcomes. So as not to unduly complicate the choice process, six elements were used in this study as recommended by King and Robison though a smaller or larger number of elements can be used. Using six elements facilitates the explanation of the choice situation to the respondents, since the probability of occurrence of any one element of each distribution may be equated to the probability of obtaining a specified number of dots on rolling a die. As a rule, the distributions are defined over a narrow range of outcome levels since the decision maker's absolute risk aversion can then be assumed to be constant over that range. The four net farm income levels selected for this work are $5000, $14 000, $23 000 and $32 000, based on abstractions from ABS (1993) statistics of expected pre-tax net farm income in the Barwon district between 1990 and 1993. According to the survey, 12.5 per cent of producers earned $5000 or less over the period, 25 per cent below $14 000, 50 per cent below $23 000 and 75 per cent below $32 000. These were therefore considered feasible average earnings for the farmers in the study.

Following the ordering of the pairs of distributions for various upper and lower bounds of the absolute risk aversion function, a questioning procedure is then designed to elicit the respondent's preference interval. The questionnaire is in the form of a programmed learning text in which the respondent is guided through a hierarchy of pairwise comparisons designed to continually increase the precision of interval measurement. The questioning procedure allows the elicitation of the decision maker's absolute risk aversion range at some specified level of income. Details of the mechanics of the procedure are provided by King and Robison (1981a,b). In the current study, practice sessions were conducted until the respondents showed some understanding of what was required. This was done in recognition of the Hogarth (1975) observation that farmers generally lack expertise with regard to the expression of opinions in probabilistic terms.

Based on the ABS (1993) survey results reported above, the four income levels of $5000, $14 000, $23 000 and $32 000 were chosen for this study. Direct interval measurements were made in the neighbourhood of these income levels and the formulated distributions are provided in Appendix A2.

4.6.1 Preference interval results

The object of the measurement was carefully explained to each farmer by using the analogy that each of the six elements of a given distribution may be seen as the numbers that turn up on the toss of a die. This was easily comprehended and the farmers were then requested to make their choices between the derived distributions. A summary of the results of the farmer preference interval measurements are given in Table 4.3. The choices made in each income group enabled narrowing of the preference interval for each farmer. The results reported in Table 4.3 indicate the risk attitude of the five respondent farmers to be varying levels of aversion to risk from slight to moderate. For farm one for instance, the elicited preference range indicates that for this farmer, the marginal utility or satisfaction from an additional dollar is decreasing at the rate of between 0.01 to 0.001 per cent for each dollar increase in net farm return. For farm five, the elicited infinite upper bound on the farmer's risk aversion implies that at higher income levels the farmer is more risk averse than at lower income levels. As noted by Love and Robison (1984), this may be expected as individuals are usually willing to take added risk at low income levels given the small magnitude of the absolute dollar amounts as well as the variability of the paired distributions. These elicited intervals (Table 4.3) were used as the lower and upper bounds of farmers' preferences in the programming models constructed for this study.

To serve as a check of the derived preference ranges, the non-negative certainty equivalent approach suggested by McCarl and Bessler (1989) was used to determine an upper bound of risk aversion for each respondent farmer. The approach suggests that an upper bound for the absolute risk aversion coefficient for an individual can be established such that certainty equivalent disregarding wealth is non-negative. Based on the approach, the upper bound is computed using the following expression:

$$r_a < 2^*E(NR)/\sigma^2(NR)$$

where E(NR) is the expected net revenue and σ^2(NR) is the corresponding variance of the most common farm portfolio which was taken to be the observed farm plan for the case farms. The determined upper bounds which are above the elicited upper ranges, are given in Table 4.4. It is to be noted that the upper bounds of r_a determined using the non-negative certainty equivalent approach were generally higher than the elicited values shown in Table 4.3.

Table 4.3 : Elicited producer preferences for pre-tax net incomes between \$5000 and \$32 000 using the interval approach[a]

Respondent	Section	Preference interval Upper, r_1	Lower, r_2
Case farmer one	1	0.0001	0.00001
	2	0.0001	0.00001
	3	0.0001	0.00001
	4	0.0001	0.00001
Case farmer two	1	0.0001	0.00001
	2	0.0001	0.00001
	3	0.0005	0.0001
	4	0.0005	0.0001
Case farmer three	1	0.0001	0.00001
	2	0.0001	0.00001
	3	0.0001	0.00001
	4	0.0001	0.00001
Case farmer four	1	0.0006	0.0001
	2	0.0006	0.0001
	3	0.0001	0.00001
	4	0.0001	0.00001
Case farmer five	1	0.0001	0.00003
	2	0.0001	0.00003
	3	0.0001	0.00003
	4	∞	0.0003

[a] Based on responses to Appendix A2.

Table 4.4 : Upper bounds on farmer risk-aversion coefficients using the non-negative certainty equivalent approach

Case farm	Upper bound for r_a
One	0.000325
Two	0.000610
Three	0.000107
Four	0.000434
Five	0.000299