Chapter 4

HOLISTIC STOCHASTIC MODELLING IN FARM BUSINESS MANAGEMENT

4.1 Introduction

As stated in Chapter 1, Holistic Dynamic Modelling (HDM) is an approach for sustainable planning that takes into account model dynamics, feedback processes and the stochastic nature of the operation of the system as essential conditions for strategic management. Modern management accepts that it must manage the instability of the organisation. Analytical methods can be used to minimise this instability and contribute to a better decision-making environment and this is the aspect explored in this chapter.

Instability is included in the general area of risk and stochastic processes, and therefore this chapter commences by outlining the concepts of risk, types of risk, risk analysis and risk management incorporated into decision models. The chapter finishes with a description of how the holistic stochastic modelling criterion considered in this study might be applied to managing instability in the farm system.

4.2 A Basic Understanding of Risk

Basically, understanding risk in agriculture comes from accepting the uncertain environment in which agriculture operates and its inter-relationship to farm income, resource allocation problems, sustainability and the policy choices for resolving these instability problems (Fleisher 1990). When analysing agriculture in a systematic manner it is possible to observe uncertainty everywhere. There are factors internal to the farm, ranging from ecological and production processes (i.e. climate, genetics, soil quality, management, etc), through to resource allocation and resource quality control (i.e. physical, financial and human) and attitudinal characteristics of the decision maker that create a truly uncertain environment. External farm conditions (i.e. marketing situation, taxation policies, rate exchange and interest rate) also have a direct effect on farm business performance.

The management of uncertainty is an integral element of farming activity. Production decisions have to be based on distributions of prices, yields and animal performance, amongst others, rather than single-value functional relationships. Therefore, farm business management is essentially a process of managing uncertain relationships. Decision makers face daily a risky environment where not only the internal components of the system but also those of the external environment are uncertain. It follows that risk is a normal variable which should to be taken into account in whole-farm planning in a practical way, a way that caters for the uncertainty in performance of a system where risky decisions inevitably need to be made.

According to Hamilton (1994), risk exists as a normal component of each human activity system---consider analysing, for example, the specific fields where "risky" situations may be identified: natural hazards, social hazards, financial hazards, technological hazards. A challenging aspect for understanding the sources of risk comes from analysing risk components and what constitutes risk (i.e. resources, threats, consequences, influential factors). Risk derives from managing tangible resources within a changeable environment, where threats may produce definitive consequences that modify the target outcome in a negative manner, and opportunities increase the scope of better organisational performance.

To understand risk and its origin it is necessary to evaluate the risk situation within the management environment. The inherent uncertainty of agriculture makes it a risky business, and, depending the source of the uncertain event, there may be specific categories of risk. Each type of risk will have particular effects on the organisational process of the firm and the manager's attitude, and each type of attitude will produce a particular management response. Figure 4.1 extends the description of the sources of risk to identify risky elements from the economic environment, financial environment and biological environment all of which combine to define a typical risky farm operating environment. On the opposite side of the diagram are the socio-political and human components that represent atypical risk.

A basic understanding of risk in organisational management implies a clear perception about the meaning of risk, the types of risk that the decision maker has to cope with, and the tools provided to analyse and manage risk situations, and so these topics are now elaborated.

4.2.1 Risk definition

Definitions of risk are abundant (Dillon 1977, Dillon and Hardaker 1980, Anderson, Dillon and Hardaker 1977, Hazell and Norton 1986, Barry 1984, Fleisher 1990 and Ritchie and Marshall 1993). Authors tailor their definitions to

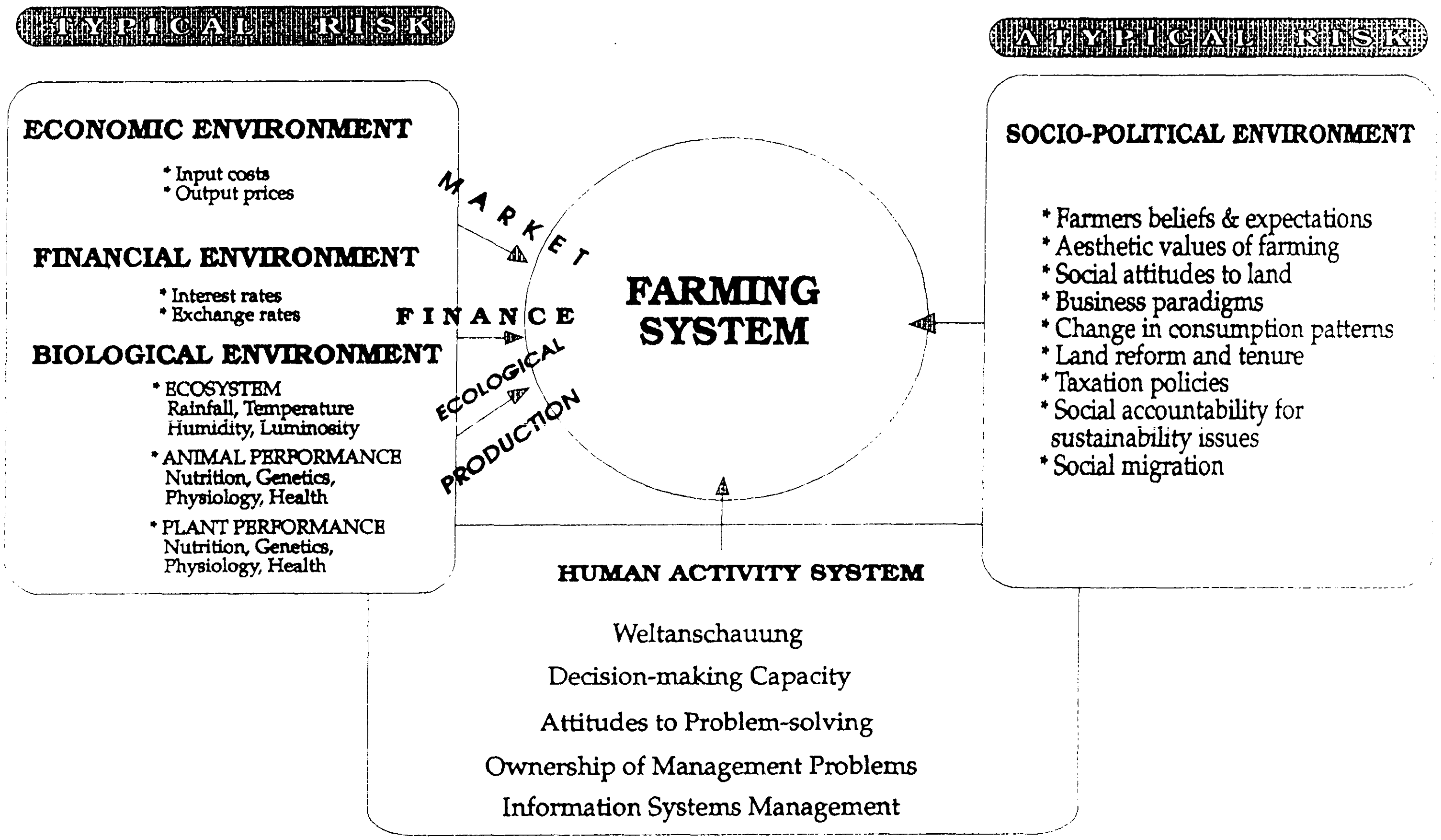

Figure 4.1 Sources of Risk and Uncertainty in the Farm System
Source: Charry (19)4)

fit within their particular viewpoint on risk analysis and management.

Dillon (1977, p.102) argues that risk involves a personal or subjective judgement both about the chances associated with the different possible outcomes that may arise from any particular choice, and about preferences between the set of possible outcomes that are associated with alternative choices. Because these elements involve subjective judgement, operating conditions that would be appropriate for one decision maker may be quite inappropriate for another. Fleisher (1990, p. 13) defines risk by analysing the environment that creates risk. The consequences for decision makers often depend both on the actions they choose and on future events that are beyond their control.

As Figure 4.2 shows, it is possible to generate a simple definition of risk which explains risk as the intersection between certainty and uncertainty from a managerial perspective. Five components characterise this risk perception:

(a) Influence of decision control on threats;
(b) Measurable likelihood of expected outcomes;
(c) The value and influence of knowledge from the side of the decision maker;
(d) The critical value of management information systems; and
(e) The targeting of maximisation of opportunities.

After these elements are integrated with those from Fleisher (1990), Ritchie and Marshall (1993), Anderson (1994), Hamilton (1994) and Madden (1994), several definitions, with an emphasis on organisational management, may be elaborated, as follows:

(a) **Risk** is managerial decision making with a relatively controllable and measurable set of likely outcomes.

(b) **Risk** is uncertainty that is controllable to some degree, allowing the decision maker to define the likely outcomes with some level of statistical

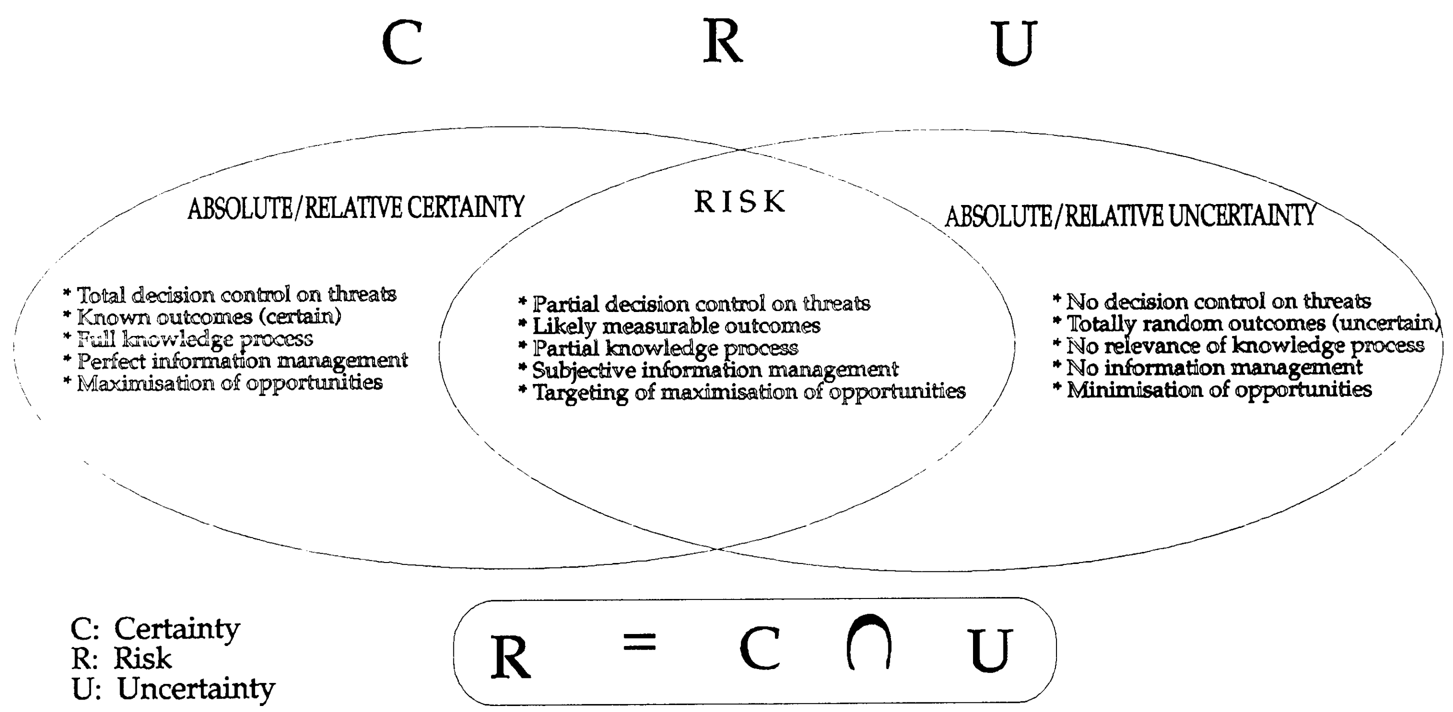

Figure 4.2 Integration Between Certainty, Risk and Uncertainty
Source: Charry (1994)

confidence.

(c) **Risk** is a challenge to the decision maker to manage decision problems towards the least uncertain outcomes.

(d) **Risk** is in simple terms the management of the variability that affects outcomes which may be defined in statistical terms in uncertain environments.

(e) **Risk** is the management of controllable uncertainty in order to minimise the probability of unsuccessful managerial decisions. Threats and opportunities interact with each other to define the risky environment of the management problem.

(f) **Risk** is the management of uncertainty with measurable consequences (Anderson 1994).

(g) **Risk** is the manipulation of those factors which are probably controllable and threaten management target outcomes.

(h) **Risk** is a situation in which the resolution of uncertainty will affect the wellbeing of the firm and the decision maker and one which involves the chance of loss or gain. Negative consequences (losses) that may result from risk events are in general referred as "**downside risk**" and positive consequences (gains) from risky events are refereed as "**upside risk**" (Fleisher 1990).

(i) **Risk** is the boundary between certainty and uncertainty on the basis of the amount of information available to the decision maker (Knight 1921).

(j) **Risk** is an element in farm business which cannot be eliminated. It is a managerial factor that increases the scope of better controlled decision making processes.

For a better understanding of the above definitions it is necessary to explore the concept of *deviation*. Nominal deviation, absolute deviation and square deviation are the foundations of further complex techniques widely used in risk analysis.

From a statistical point of view, descriptive statistics provide methods to summarise data, so that they are easily manipulated and comparable with one another. The techniques for doing this are called measures of central location (of which the mean is the most important statistic) and measures of dispersion (of which variance or standard deviation is the most important statistic). Their inter-relationship constitutes the central focus of statistical analysis. Measures of central location provide a reference point or "target value" for decision making. Measures of dispersion provide the opportunity to quantify the degree to which the observations (performance outcomes) are spread out about this reference point or target value. The difference between an average or target value and performance data is called the *statistical deviation*. This is the concept which is most fundamental to risk. The variance (or standard deviation) is an unambiguous, single dimensional index of risk (Young 1984, p.34). Therefore the first element of risk analysis is the measuring of variability (deviation) against a reference point (target value). But of course, risk is more than that. As defined by Fleisher (1992 p.22) risk itself does not simply equate to variation but, rather, unexpected variation. This brings in the concept of probability in the basic definition of risk. When the decision maker perceives the holistic nature of the decision-making environment and the uncertainty of the decision processes,
the elements of probabilistic distributions (relatively controllable uncertainty) need be linked to the primary risk concept from a statistical point of view, in order to have a holistic understanding of the phenomenon. Under this assumption risk is represented by a vector of all the moments of the probability distribution. Therefore it may be said that risk, from a statistical point of view, is basically the management of unexpected variability (related to a target) within assignable levels

of confidence (probability distribution of outcomes).

Further information about descriptive methods (with special emphasis on mean, variance, standard deviation and coefficient of variation) may be found elsewhere (e.g. Keller *et al.* 1994 pp. 11-214 and Selvanathan *et al.* 1994 pp. 39-77).

4.2.2 Risk Classification

In an overview of sources of risk in the farming system it is possible to classify farm risk broadly into both typical and atypical categories, as indicated in Figure 4.1. Typical risk encompasses events for which probability density distributions or subjective probability values may be worked out. This type of risk is considered in the economic, financial and biological environments of the farming system. There are other factors that not only escape the farmer's control but also, and chiefly, cannot be accommodated in planning models, since it is not possible to define any suitable set of manageable data. These factors encompass atypical risk, and relate to socio-economic aspects of the internal and external farm environment and the specific influence of humans when decision-making processes are undertaken. It is possible to explicitly account for this type of risk using simulation procedures such as systems dynamics (Gill 1995).

It is commonly accepted that risk can be broadly classified into three categories, as follows:

(a) *Production risk* which comes from the dynamic interaction of the farm resources in the system performance. The farming activities (i.e. enterprises) constitute the way the resources of the farming system are transformed into purposeful outcomes, through the process of production. Natural conditions (i.e. rainfall, drought, sunlight, soil fertility, etc) and biological conditions (i.e. nutrition, genetics, reproduction and health) of the living species that transform the farm resources to physical outputs are examples of this type of risk. Risk associated with input costs may either be considered here or in the marketing risk category. Critical variables of constraints of the farm system may be identified, and, instead of using discrete values, probability distribution values may be incorporated within a model.

(b) *Financial risk* which comes from the influence of capital resources on farm system operation. Payments for productive resources, assets and loan servicing affect the financial position of the farm system.

(c) *Marketing risk* which comes from trading the farm commodities. Variability in farm commodity prices is one of the major aspects that create a wide variance between planning outcomes and final farm financial performance.

In another formulation of these concepts Bertelsen (1985), Parton (1989) and Parton and Cumming (1990), categorise risk at two levels based on the source of farm income variability:

(a) *Business risk* which is derived from production risk, results from the biological variation of the production process, and the market variation of input and output prices. Price and yield variability differ between agricultural commodities. Therefore, the amount of business risk that farmers face is affected by their selection of farming enterprises. Within this scheme, biological variability is considered in the planning model through the changes that it produces in the financial outcome of the enterprise and it is commonly defined by the coefficient of variation of the expected income (Parton and Cumming 1990). No direct consideration in the risk setting is given to the biological variables by these authors, but only the consideration of their effect on the financial outcomes.

(b) *Financial risk* which refers to the additional variability of farm earnings resulting from fixed financial obligations associated with debt financing and cash lending. Selection of a debt profile affects the financial risk confronted by an agricultural producer.

The analysis of the first and second levels of resolution of the conceptual maps of the farm system described in Chapter 2 can be extended to a third level of resolution in order to explore the factors that create instability in the dynamics of the system. As such, the detailed conceptual mapping of a system will often reveal added sources of risk that can subsequently be represented in formal risk programming models. Figures 4.3, 4.4 and 4.5 show a third level of conceptual mapping when the analysis is undertaken from the perspective of the farm resources, production enterprises and the decision maker (environment of the system) for purposes of risk identification.

In summary, the three conceptual maps that were organised for the purpose of identifying stochastic elements in the farm system show that there are operational and human elements that work to create uncertainty in the dynamic action of the system. These elements are classified as "***technical risk***" and "***attitudinal risk***" for the purposes of this study and are progressively endorsed in the farm mapping exercise.

Technical risk encompasses four risk subgroups related to each of the system components, production processes, financial aspects and marketing situations that may be quantified without difficulty and incorporated in the input-output parameters of mathematical programming models. Some ecological components of the farm environment can be incorporated into the quantitative matrix of a programming model through their effect in production (e.g. rainfall, soil fertility, etc).

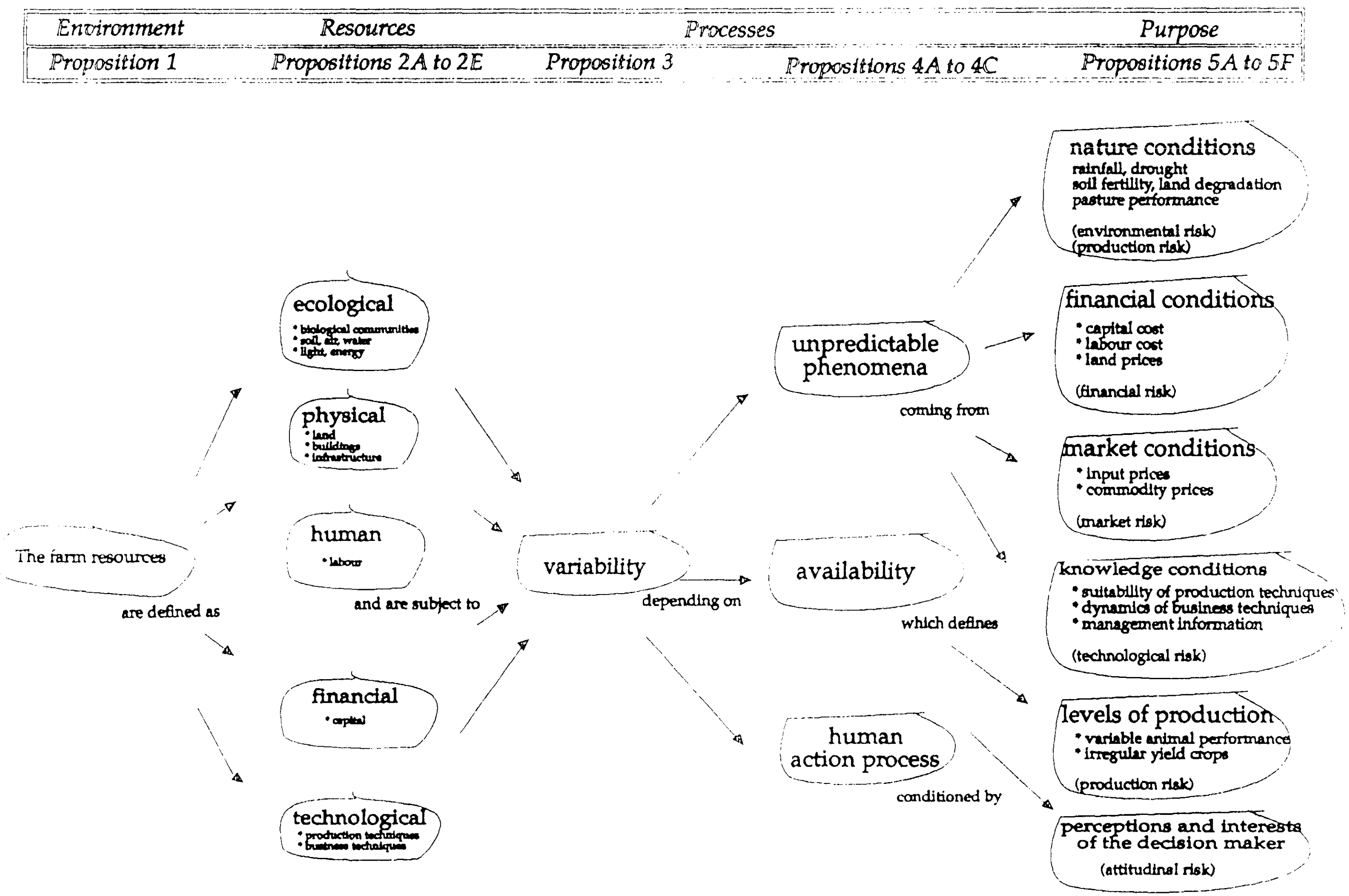

Figure 4.3 Third Level of Resolution of Conceptual Mapping for Farm Resources: Purpose of Risk Identification

Environment	Resources	Processes	Purpose
Proposition 1	Propositions 2A to 2E	Propositions 3A to 3E	Propositions 4A to 4B

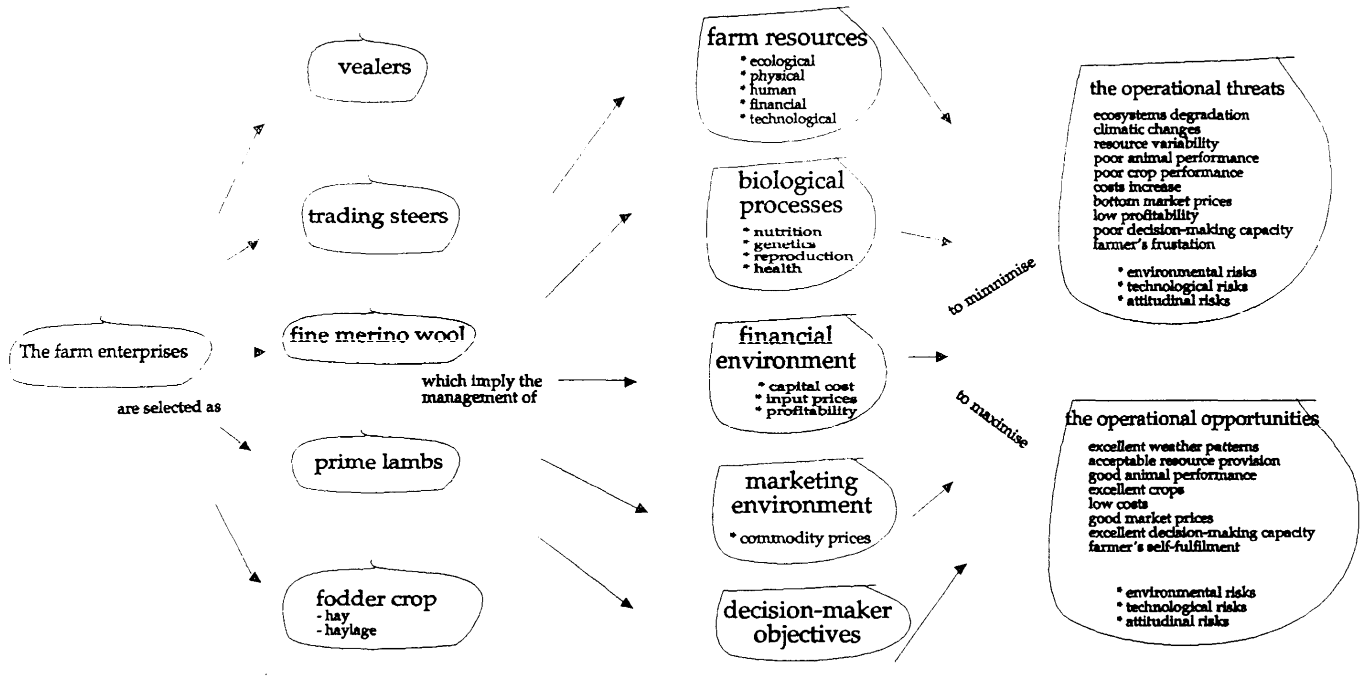

Figure 4.4 Third Level of Resolution of Conceptual Mapping for Farm Enterprises: Purpose of Risk Identification

Environment	Resources	Processes		Purpose
Proposition 1	Propositions 2A to 2D	Proposition 3	Propositions 4A to 4G	Propositions 5A to 5E

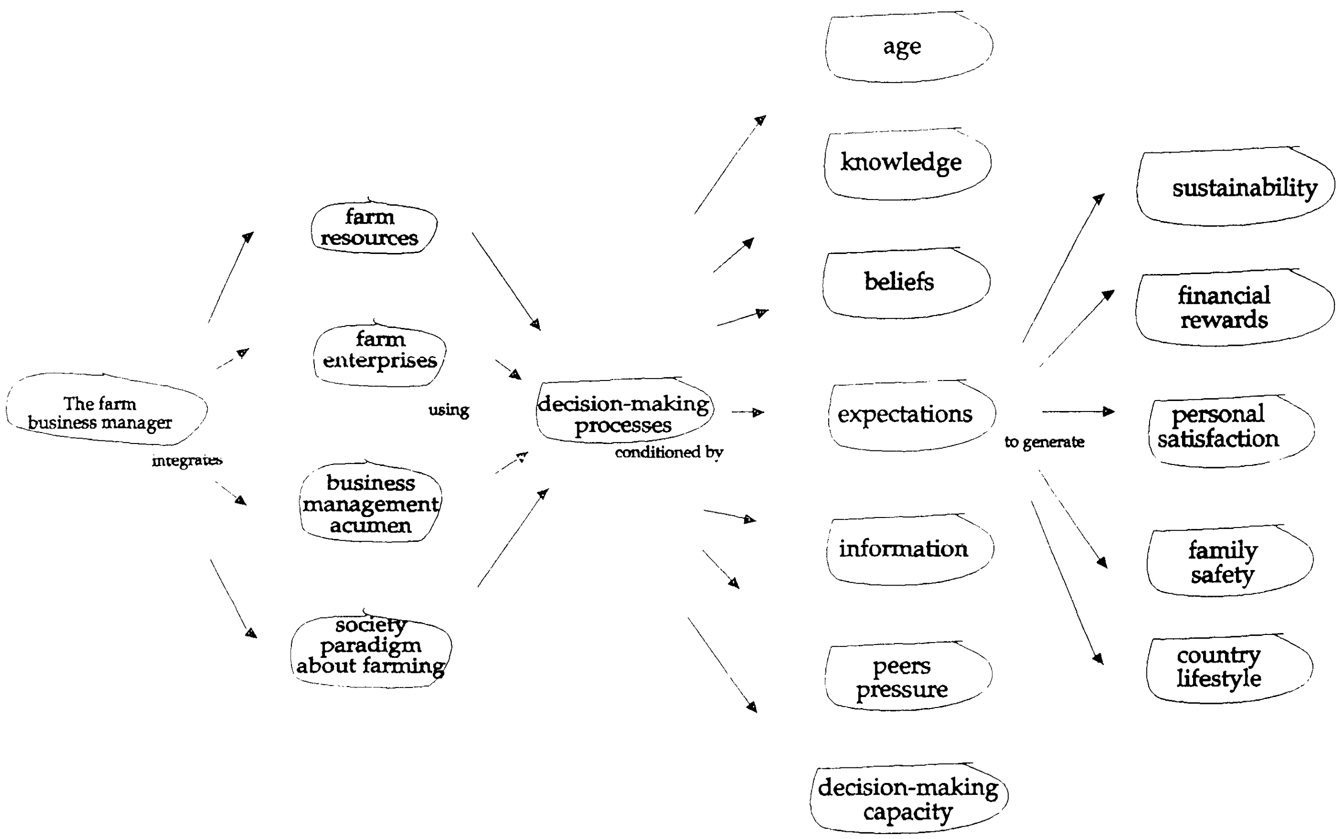

Figure 4.5 Third Level of Resolution of Conceptual Mapping for the Farm Business Manager: Purpose of Risk Identification

There is an element of risk in the decision-maker's attitude towards understanding and managing farm resources, their inter-relationships and feedback processes to control the factors that create instability in the farming system operation. This element of uncertainty in the farm system operation has been labelled as *attitudinal risk.*

The influence of the decision-maker's attitude (i.e. attitudinal risk) in the farming activity has been treated in different ways by different authors depending on the framework of analysis. In organisational dynamics, after Stacey (1993), attitude is a dynamic element that generates creativity and contingency positions in the decision maker which reinforce the purposiveness of the system as a human activity system, a typical soft systems statement. From the perspective of OR (i.e. hard systems thinking) the risk attitude is simply a value of performance which is quantified through a utility function of a different shape, depending on the degree of preference for risk of the decision-maker. Loomba (1978, p. 30) describes three attitudes to risk supported in the concept of marginal utility. They are risk aversion (i.e. quadratic functions), indifference to risk (i.e. linear functions), and a desire for risk (i.e. exponential functions). After Anderson, Dillon and Hardaker (1977) the implementation of these relationships became an important element in decision theory. Lately, several authors have incorporated new algorithms in decision making under risk where a quantification of the decision maker's risk attitude is not required since previous assumptions of behaviour are established (i.e. risk aversion for quadratic programming; Zangwill (1969); Taha (1982); Lee *et al.* (1985); risk aversion and risk preference integrated throughout the different domains of the utility function as in Patten, Hardaker and Pannell (1988) and Lambert and McCarl (1985). Other authors simply ignore or criticise the approach as impractical and build on alternative algorithms (Hazell 1971; Tauer 1983; Parton and Cummins 1990, Weiss 1994).

4.3 Risk Analysis and Risk Management in the Context of Decision Making

The analysis of decision making under risk may be handled in several ways. Lee *et al.* (1985) consider that the environment within which planning decisions are made is often categorised into four states: certainty, uncertainty, conflict and risk. Deterministic traditional planning methods offer "certain" solutions to the system because the values used in the planning horizon are assumed to be certain. A state of "uncertainty" refers to a condition where the probabilities of occurrences in a decision situation are not known. The theory of games is concerned with decision making under "conflict". Decision making under risk offers a two-fold analysis, combining decision theory (where an elicitation of the decision maker's utility function is undertaken or assumed), and other methods (which do not take into account the value of the decision maker's utility function) but use a safety-first approach (Parton 1989). Safety-first models were initially proposed by Roy (1952) and Telser (1955) and are designed to help ensure that farmers attain the minimum income necessary to meet farm costs. Many of the safety-first decision rules applied to business decision making have as their basis a preference for continued survival first and a profit-oriented objective second (Hazell and Norton 1986). Safety-first rules have considerable intuitive appeal. They require the decision maker to specify just the disaster region and the probability of entering it that the farmer would find acceptable. A disadvantage, however, is that a very profitable option may be excluded because it just fails to achieve the minimum probability value threshold (Parton 1989).

Under risk, the outcomes of a decision situation are defined either by a probability distribution based on previous information or by subjective probabilities; under uncertainty, no probabilities can be determined. As such, certainty and uncertainty represent the two extremes of a continuum of available information, with risk as a point in between, as previously explained in Figure 4.2. There are no clear boundaries in the literature between the concepts of risk analysis and risk management; and therefore this chapter defines a reference point so a set of concepts may be used consistently throughout the study.

With reference to this conceptual mapping exercise, risk analysis and risk management in the context of decision making (i.e. the system environment) identify an array of decision-making possibilities - i.e. under certainty, uncertainty, conflict and risk - which are the resources of the system. These possibilities are implemented through a managerial framework - planning, organising, implementing, controlling and evaluating -- which form the system processes that allow risky situations to be quantified (i.e. risk analysis) and risky situations to be overcome (i.e. risk management). The dynamic of this risk system definition is developed through propositions and inter-relationships visualised in the conceptual map in Figure 4.6.

Risk analysis, then, can be understood as the application of the set of analytical techniques to measure risk in managerial decision making, using evaluation, qualification and quantification of a risk situation. Because managerial decision making is implemented throughout the management process, risk analysis may be carried out before an action is taken (planning), during a management process (organising, implementing and controlling), or at the completion of some activity (evaluating).

Methods of risk analysis range from fundamental applications of descriptive and inferential statistics through to decision theory and safety-first approaches. Several methods have been developed within the last framework. Because the theoretical implementation of risk analysis and risk management requires an in-depth review it will be discussed under a specific heading later in this chapter.

Most risk problems have been confined by an analysis which evaluates income variability directly. The implicit assumption widely accepted among planners and researchers is that the incorporation of risk analysis in enterprise planning models should be done through the financial variables of the system (i.e. prices of commodities or gross margins of enterprises). However, stochastic farm

Environment	Resources		Processes		Purpose
Proposition 1	Proposition 2	Proposition 3A-3D	Proposition 4	Propositions 5A to 5E	Propositions 6A to 6B

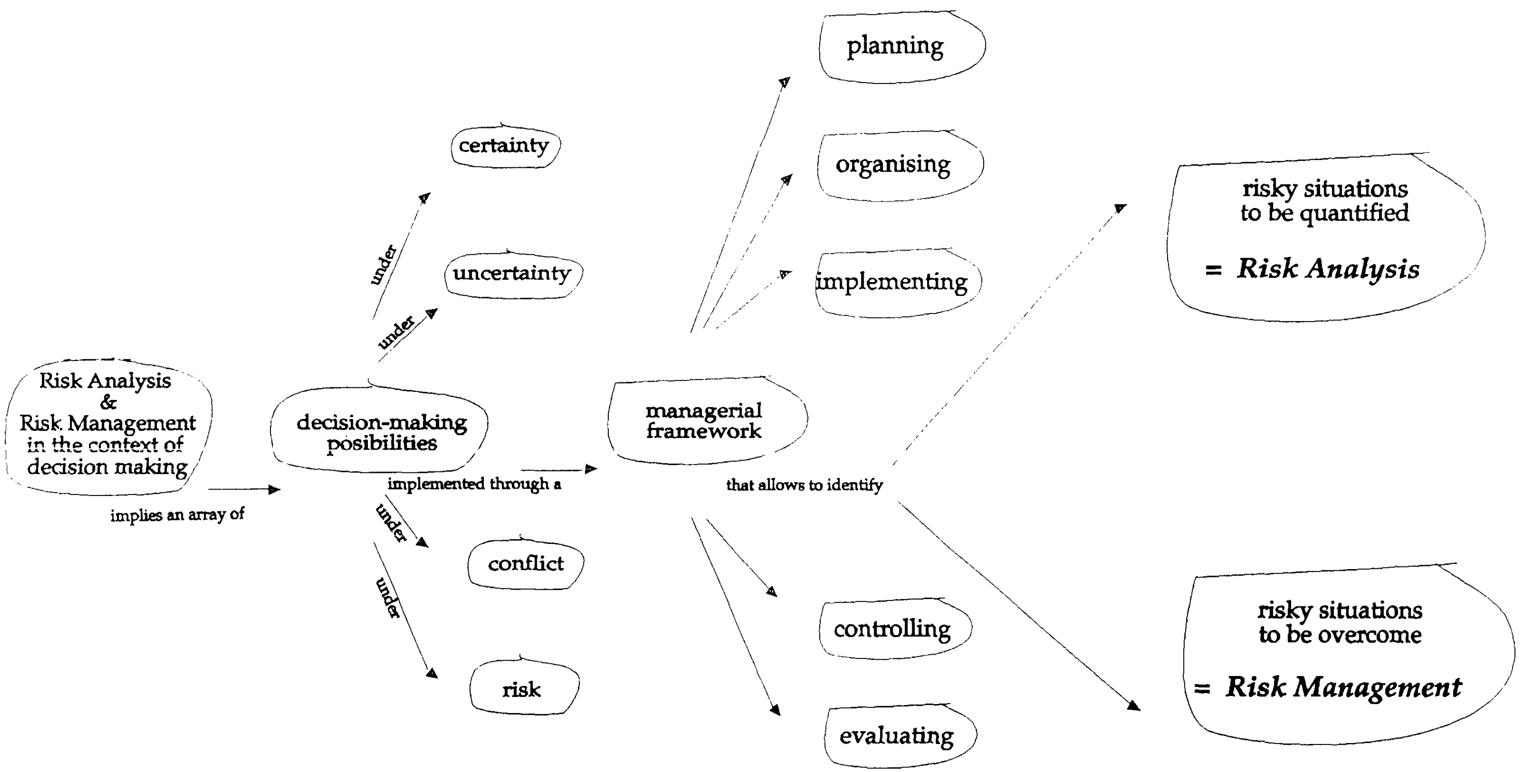

Figure 4.6 Conceptual Map of Risk Analysis and Risk Management

planning models may be specified which allow for probabilistic variation in other types of model variables (Wicks and Guise 1978). This will be explored further in this study in order to find a more flexible approach to the management of farm system volatility through parameters that do not necessarily invite conversion into financial variables.

Risk Management, on the other hand, becomes the implementation of decisions under risk where analytical and empirical tools are used in order to minimise the probability of threats (downside risk) and maximise the probability of opportunities (upside risk). Risk management implies that decisions and strategies are taken to address a risk situation. There are broadly speaking two choices: theoretical quantitative models and empirical conceptual models. Figure 4.7 gives an overview of risk management which examines types of risk as undertaken by this study. Under each managerial function the overview assigns relevant quantitative and empirical methods. Note that although quantitative decision models are available for most managerial functions they are limited in their use to farm system planning.

Figure 4.8 summarises, under the management functions, quantitative and empirical options for operational risk management. This figure is only an example, and does not exhaust the set of possibilities that the decision maker may use to solve management problems in a stochastic environment.

4.4 Decision Criteria for Risk Management in Decision Models

The available tools for risk measurement and management in decision planning models integrate mathematical and statistical algorithms that have been developed to incorporate risk in farm models. Two areas can be distinguished, here: decision theory, which is based on expected utility models and subjective probabilities, and the safety-first approach, which does not require prior information on the utility function of the decision maker. Parton (1989) stresses that risk-oriented decision criteria have two main considerations: firstly, the risk

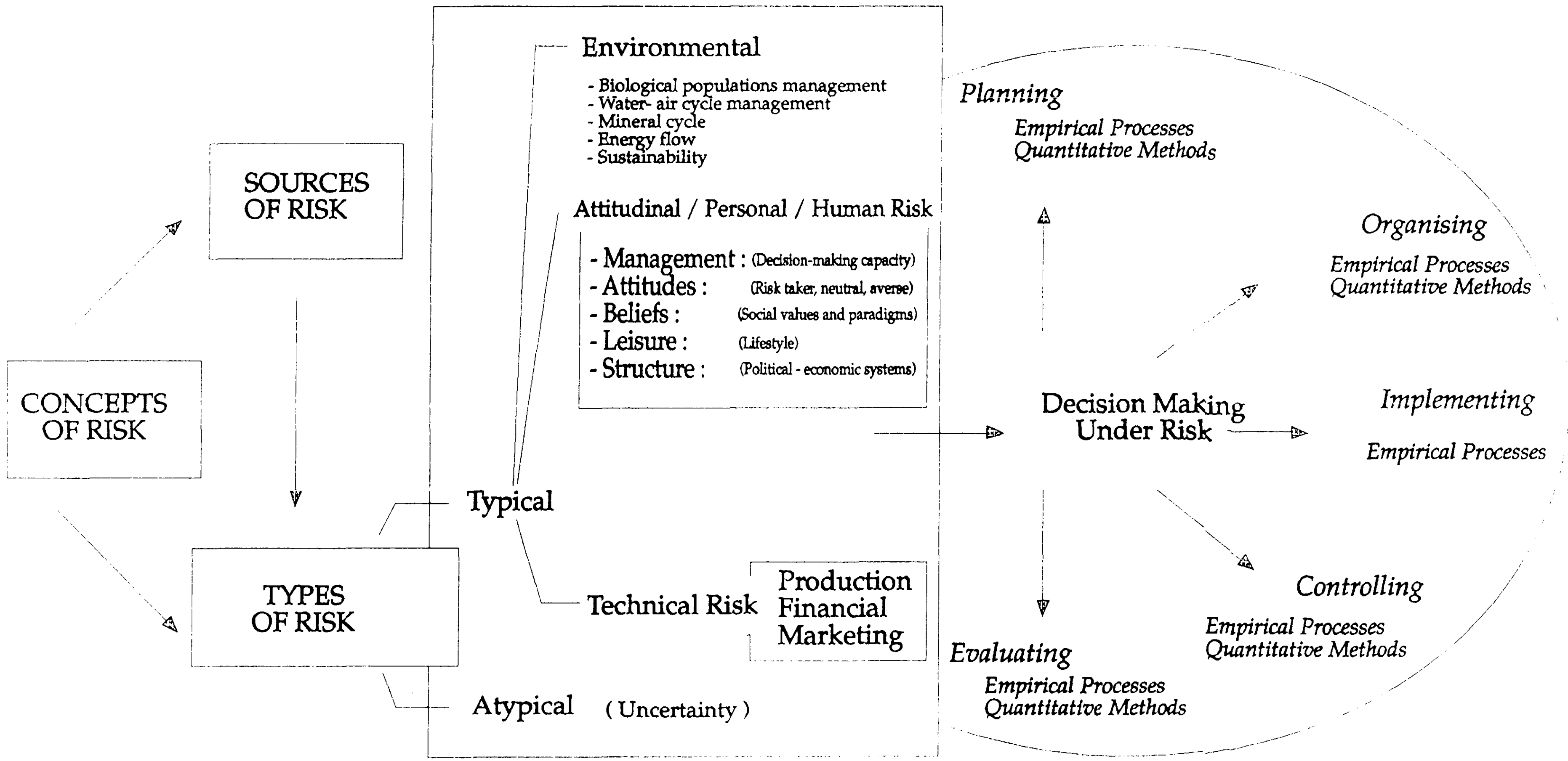

Figure 4.7 Risk Analysis and Risk Management in Organisational Management

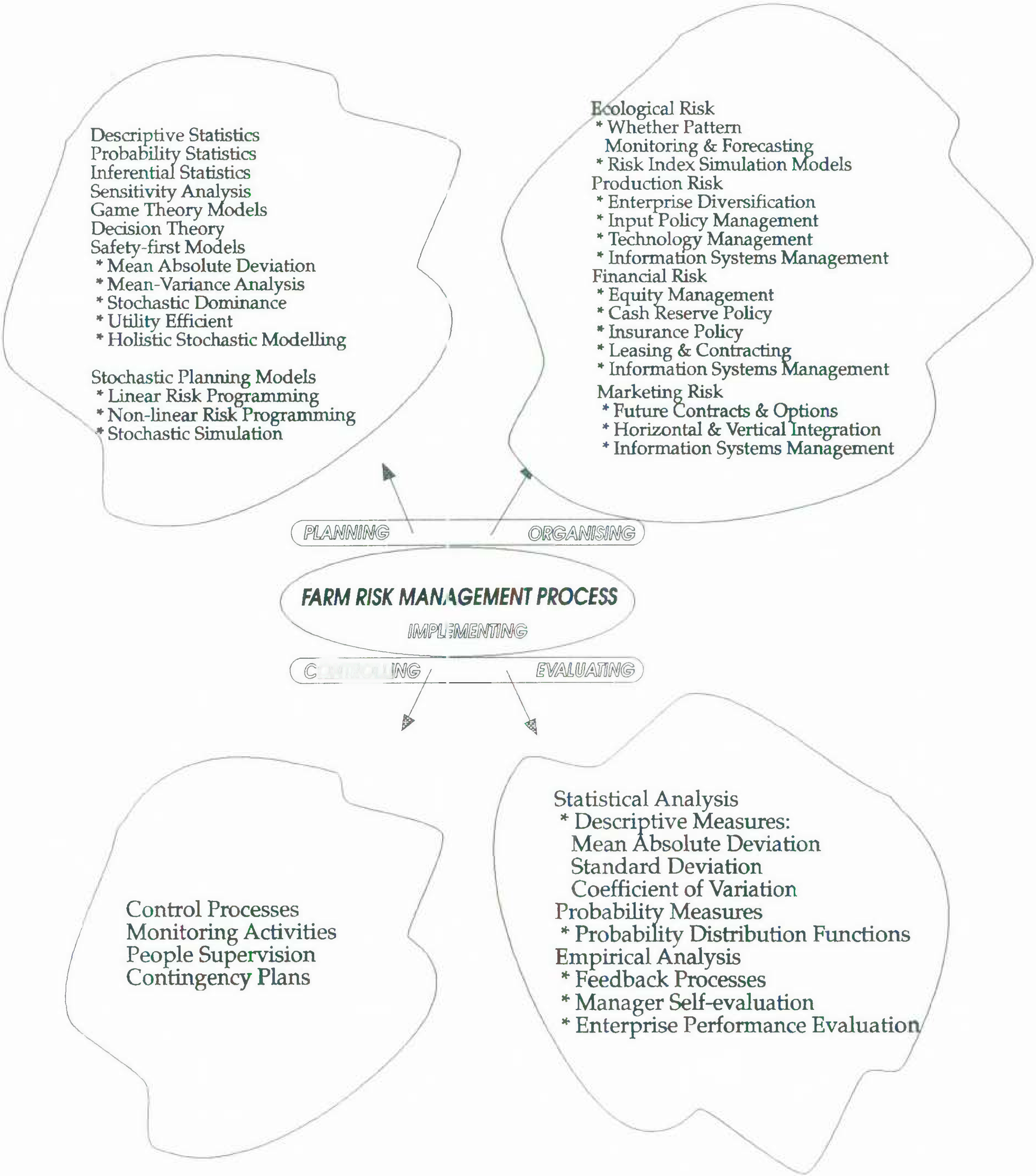

Figure 4.8 Operational Risk Management in the Farm System

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aversion attitude of the decision maker, and secondly, the decision maker's perception of risk. Groebner and Shannon (1992) elaborate on these statements.

As the focus of this study, the application of *holistic stochastic modelling (HSM) criteria* to farm planning requires a review of the available alternatives to accommodate risk in decision planning models. A summary of the more relevant options follows, and then this study proposes an integration of the stochastic components of the farm system in the planning model, using concepts from various authors, to include the perceived technical risks of the case-study farmer and his/her risk attitude.

4.4.1 **Pratt (1964): (E-V) Analysis**

Anderson and Hardaker (1979) state that methods to accommodate risky constraints require sophisticated mathematical programming models, presenting considerable problems for the analyst. If uncertainty in input requirements is ignored and risk is measured only by the variance of activity gross margins, an absolute risk aversion criterion defined through a quadratic programming function is an acceptable approach (Hassam and Hallam 1990).

The (E-V) criterion proposed by Pratt (1964) is consistent with the preceding conditions, and assumes that a farmer's preference among alternative farm plans is based on expected income E(Y) and its associated income variance V(Y). This means that options under uncertain situations can be described by the combination of expected return E(Y) and variance V(Y) of the outcome. By convention, this is referred to as mean-variance or E-V analysis.

E-V analysis is founded in traditional statistical principles that may be found in Keller *et al.* (1990). Given a discrete random variable Y with values Y_1, Y_2 ... Y_n that occur with probabilities $P(y_i)$, the expected value of Y is:

$$E(Y) = \Sigma\, Y_i * P(y_i)$$

Since expected income is defined as a weighted average of all possible outcomes, it provides a measure of the central location of the distribution of the variable, but it does not indicate whether the values of the variables are clustered closely about the expected value or are widely scattered. That is, the mean (μ) or expected value $E(Y)$ of a random variable does not by itself adequately describe the random variable. Therefore, a complementary measure of dispersion is necessary.

The variance of a random variable is defined in a similar manner. Let Y be a discrete random variable with possible values Y_1, Y_2 ...Y_n that occur with probabilities $P(y_i)$, and let $E(Y) = \mu$. The variance of Y is defined as:

$$V(Y) = \Sigma(Y_i - \mu)^2 P(y_i) = E(Y - \mu)^2$$

The mathematical application of the E-V criterion is thoroughly explained by Anderson *et al.* (1977, p. 95). In E-V analysis the expected return E(Y) of any specified mixture of the n risky prospects will be of the form:

$$E(Y) = \Sigma\, q_i\, e_i$$

and a variance V(Y) of net return,

$$V(Y) = \Sigma\, \Sigma\, \sigma_{ij}\, q_i\, q_j,$$

where

q_i = units of investment or activity allocated to prospect i,

e_i = expected return per unit of investment in prospect i, and

σ_{ij} = covariance of the per unit returns from prospects i and j.

The E-V frontier is known as the efficient locus or the efficient set in E-V portfolio analysis. In Figure 4.9 the feasible set of portfolios lies on or below the E-V curve. Only the portfolio (or farm plan combination) that falls on the E-V curve is efficient in the sense that it constitutes a set or combination of resources and activities having maximum E(Y) for a specific V(Y).

Markowitz (1959) states that mean-variance efficiency is one of the most widely used efficiency criteria, requiring, as do other risk efficiency criteria, only the two assumptions of a risk averse decision maker and a normal distribution of outcomes; or that the utility function of the risk-averse decision maker be quadratic (Anderson *et al.* 1977). When these conditions are fulfilled, all the relevant information concerning the probability distribution of alternative choices is conveyed by means and variances (Barry 1984).

In operational terms E-V analysis is widely used for several reasons, including the fact that means and variances of probability distributions are easy to work with. Much applied work on portfolio analysis under uncertainty has used the E-V criterion for analytical convenience. Barry (1984) points out that perhaps the greatest strength of the E-V efficiency criterion is its use in quadratic programming. As such, its most widely used formulation states that the variance of the outcome distribution is minimised subject to the constraint that the distribution's expected value is greater than or equal to some specified value. By varying the expected-value constraint parametrically, an E-V efficient set may be identified (Barry 1984; King and Robinson 1984).

E-V models may be solved by quadratic or linear programming approximation techniques but Hazell and Norton (1986, p.80) state that there is an alternative E-V derivation technique where the farmer's utility function is assumed to be of the exponential form $U(Y)=1 - e^{-\beta Y}$ and the farmer's income is normally distributed. Consequently,

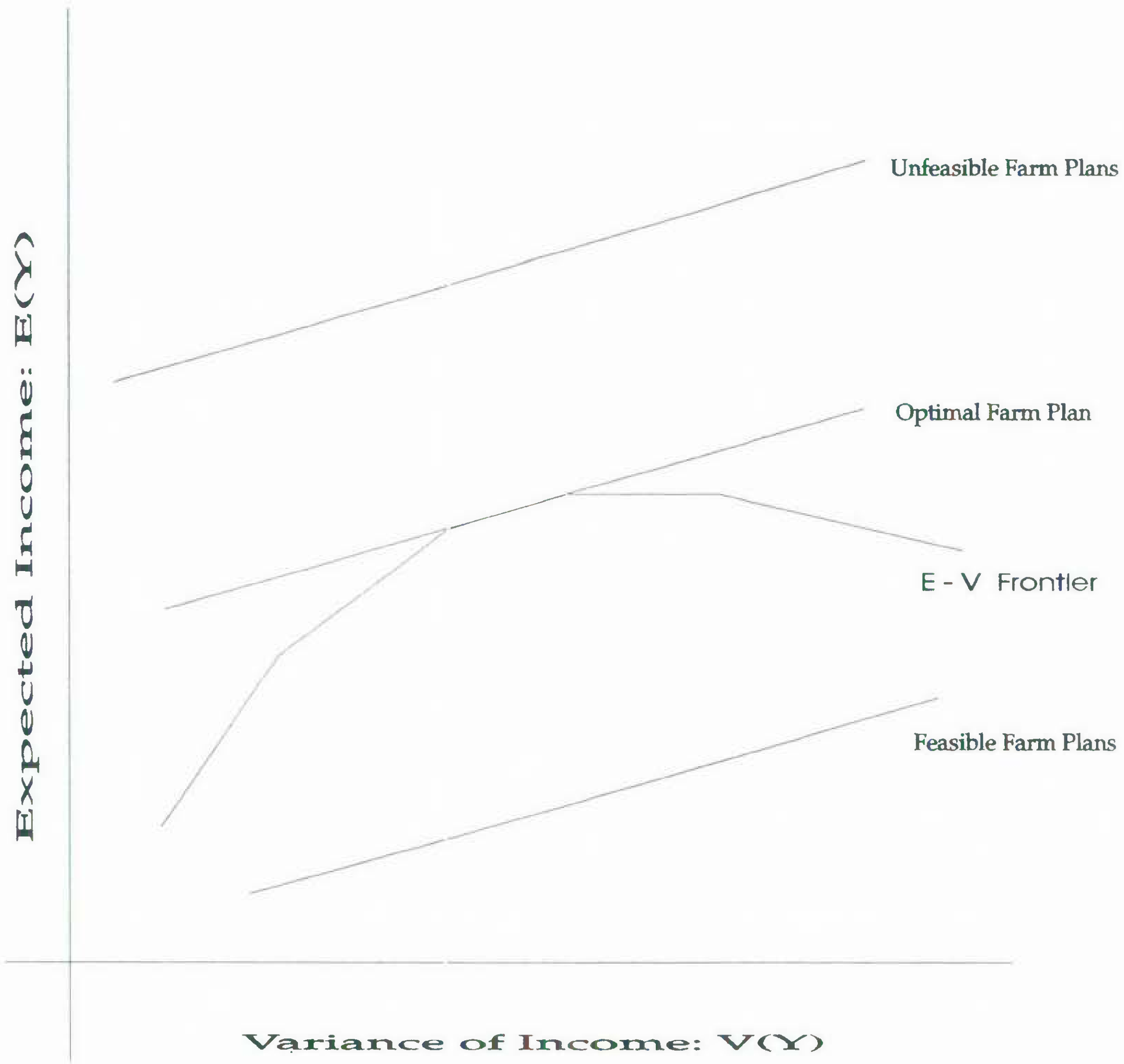

Figure 4.9 E-V Frontier for Stochastic Farm Planning

$$E[U(Y)] = E(Y) - 0.5\,\beta V(Y)$$

where

$E[U(Y)]$	=	Expected utility value
$E(Y)$	=	Expected income
β	=	Risk aversion parameter
$V(Y)$	=	Income variance

Since farm income is often an aggregate of several revenue and cost sources, by the central limit theorem, it may be approximated as being normally distributed. Therefore, a practical way to establish this is using large series of historical data in whole-farm planning.

Given an expected E-V utility function, the iso-utility curves for a risk averse farmer will be convex when plotted in E-V space. Along every such iso-utility curve, the farmer would prefer a plan with a higher variance (V) only if the mean income (E) were also greater. The farmer should then rationally choose only between those farm plans for which the associated income variances are minimum for a given set of expected income levels. The problem facing the farm analyst is to develop the set of feasible farm plans which have the property of a minimum variance (V) for an associated set of expected income levels (E). Such plans are called efficient E-V pairs and they define an efficient boundary over the set of all feasible farm plans from the perspective of Hazell and Norton (1986).

Given a set of efficient farm plans, how acceptable any particular plan will be to an individual farmer will depend on the farmer's personal preferences among various expected income and associated variance levels, as described by his/her E-V utility function. When this function can be measured, a unique farm plan can be identified which offers the farmer the highest utility. When the parameters of the expected utility function are unknown, then the best alternative seems to lie in obtaining the set of efficient farm plans and allowing the farmer to make the final choice (Hazell and Norton 1986).

Patten *et al.* (1988) argue that a quadratic utility function for income, characterised by increasing absolute risk aversion, as well as by a maximum value beyond which the marginal utility of income declines, is not always consistent with the nature of the farmer's true preferences. This makes E-V hard to accept as a suitable technique for managing risk in whole-farm planning. Tobin (1969), Tsiang (1972) and Lambert and McCarl (1985) have also questioned the applicability of E-V analysis. These criticisms are mainly related to the theoretical assumptions upon which it is based:

(a) The assumption of a quadratic utility function, while it may be convenient from a theoretical point of view, implies the unlikely event of a decision maker with increasing absolute risk aversion. It does not allow for consideration of other types of utility functions, in particular, of those for farmers who exhibit decreasing absolute risk aversion or who change their risk attitude depending on the financial performance of the farm system.

(b) The requirement of normally distributed income from risky ventures has small likelihood of being satisfied because the symmetry implied by the normality assumption may change, or may be lacking altogether. In a farm situation it is difficult to assume that returns from different portfolios would be any more than approximate to some degree to a normal distribution. However, when time series of income of established and relatively unchanged farm enterprises are used, statistical analysis is likely to derive distribution functions with a normal shape, since this algorithm is embedded in the sampling distribution of data in population analysis (Selvanathan *et al.* 1994, pp. 191-205).

(c) Stacey (1993) has suggested that variation is not necessarily a bad thing (and so should not necessarily be minimised), and may be recognised as a source of opportunity by alert managers.

4.4.2 **Fishburn (1964): Stochastic Dominance Analysis**

Stochastic Dominance or Stochastic Efficiency Analysis is a criterion by which the selection between alternative risky actions may be made when the specification of the decision maker's utility function is unknown. Formal concepts of stochastic efficiency are presented by Fishburn (1964), Hadar and Russell (1969), Anderson *et al.* (1977), Barry (1984), Parton (1989) and Fleisher (1990).

Anderson *et al.* (1977) comment that the concept of stochastic dominance has its foundations in "the Bayes strategy", where one strategy (S_1) can be checked for dominance over another (S_2) if, for all the states of nature (θ_i), utility $U(S_1|\theta_i) \geq U(S_2|\theta_i)$ and the inequality ($>$) holds for at least one state. The degree of stochastic dominance depends upon the assumptions that are made regarding the nature of the utility function (Fishburn 1964).

The concept of first degree stochastic dominance (FSD) is based upon the assumption that the decision maker's utility function is monotonically increasing and such that the decision maker prefers more to less of the outcome because s/he has a positive marginal utility. In other words, given two actions A and B, each of which have a probability distribution defined by a cumulative distribution function (CDF) of outcomes, then A is preferred to B in terms of FSD if $CDF_{(A)} \leq CDF_{(B)}$. Graphically this means that $CDF_{(A)}$ must always lie below the $CDF_{(B)}$ (Parton 1989). There are limitations associated with using first degree stochastic dominance as a decision criterion when the CDFs overlap each other at some point, because then neither function completely dominates the other. Graphically this condition means that, for FSD, the cumulated values of the dominant distribution must always lie below the cumulative values of the dominated distribution (Figure 4.10).

In Figure 4.10 $CDF_{(A)}$ dominates $CDF_{(B)}$, but $CDF_{(A)}$ and $CDF_{(C)}$ cannot be ranked, and nor can $CDF_{(B)}$ and $CDF_{(C)}$, since there are interception in the domain of the functions. This highlights the problem of the limited discriminatory power of FSD. This situation limits the usefulness of FSD, since this criterion often eliminates too few choices from consideration (King and Robison 1984).

Therefore, an additional criterion of second degree stochastic dominance (SSD) has been developed. The additional restriction of the utility function necessary for second degree stochastic dominance (SSD) is that the decision maker must be risk averse, and thus have a utility function of positive but not increasing slope. With SSD the $CDF_{(A)}$ is preferred to $CDF_{(B)}$ if the integral values of $CDF_{(A)}$ $\leq CDF_{(B)}$ for all the values of the function with at least one inequality (Parton 1989). From Figure 4.10 it is possible to conclude, using SSD, that A dominates B and C, but still it is not possible to make a clear dominance statement for B related to C, since their CDFs intersect in such a manner that a clear decision cannot be made. The undominated distributions in each division represent the efficient set of actions that would always be preferred over the dominated actions by those decision makers with a utility function that satisfies a clear risk preference criterion.

Parton (1989) points out that for some applications SSD may not be able to discriminate between alternatives well enough; therefore, the criterion of stochastic dominance with respect to a function criterion has been developed. It applies to decision makers who have a degree of risk aversion that falls within specific bounds. Meyer (1977) and King and Robison (1984) offer further details about this type of situation.

It is necessary to emphasise that in spite of its theoretical superiority over other techniques, there are weaknesses in stochastic dominance analysis that have limited its applications in farm planning. According to Patten *et al.* (1988), some of these deficiencies are as follows:

(a) Stochastic dominance procedures are not well developed for problems involving mixtures of alternatives.

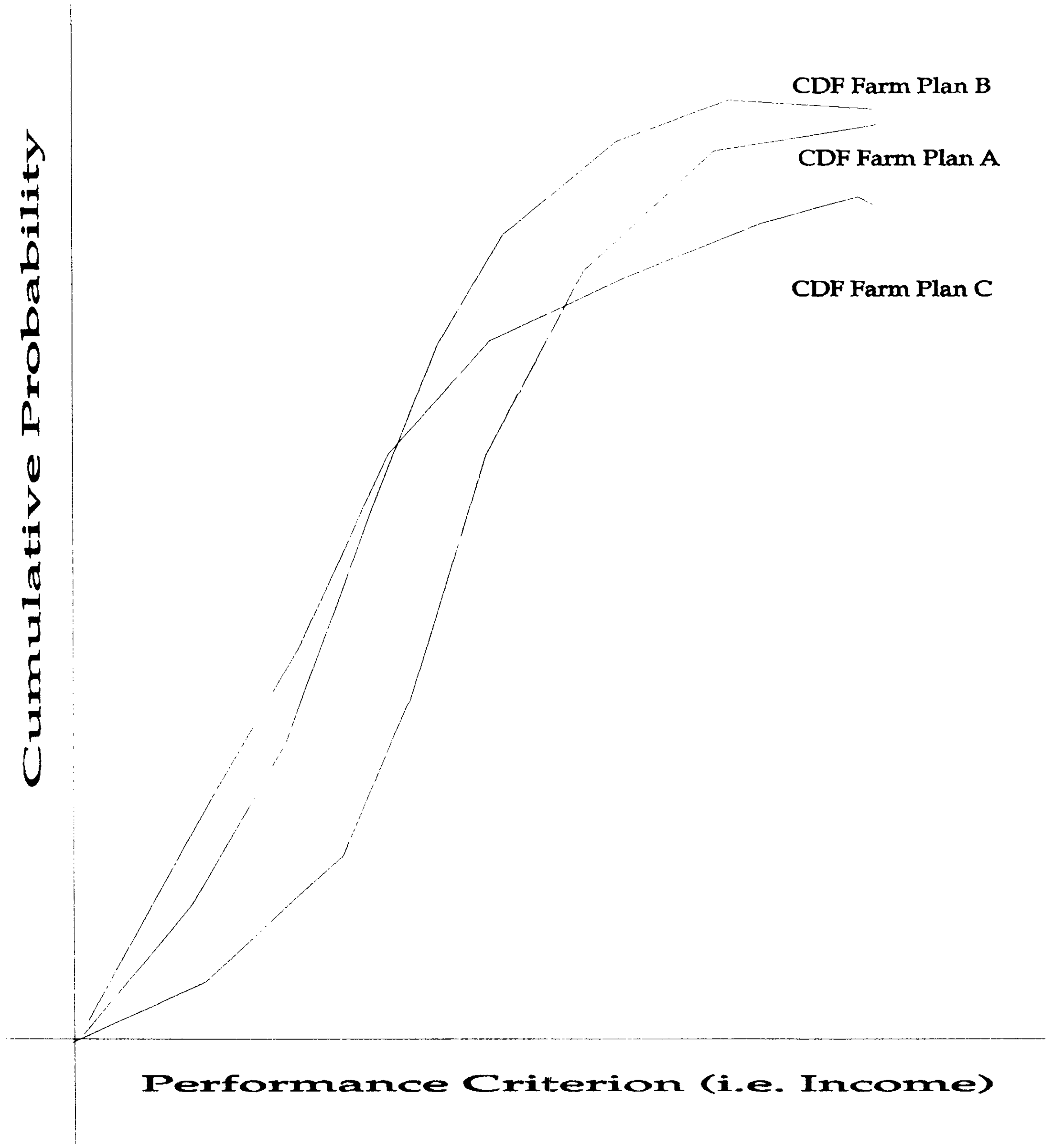

Figure 4.10 Stochastic Dominance in Stochastic Farm Planning

(b) Methods of integrating stochastic dominance analysis into mathematical programming have been limited. Specifically, stochastic dominance requires a pair-wise comparison of options, which does not make it well suited for use in mathematical programming.

(c) In reality, farmers are likely to exhibit a varying degree or polarity of risk preference, conditioned by dynamic feedback from all manner of internal and external factors operating within the farming system.

4.4.3 Cock (1968) and Rae (1971a,b): Discrete Stochastic Programming

Discrete Stochastic Programming involves the simultaneous generation of all possible outcomes and hence the transference of all variability into the objective function of a programming model (Cock 1968, p. 72). It solves a problem where all the functional restraints and input-output coefficients are subject to discrete probability distributions matched to the functional objectives of the farm system.

The corresponding discrete stochastic linear problem is formulated introducing a probability distribution into the model. The assumption is that maximisation will be carried out under certainty and by associating each resulting program with the prior distribution of outcomes defined by the probability of the underlying environment and organised in a multi-stage procedure. The general model of discrete stochastic programming is based in chance-constrained programming (Charnes and Cooper 1959) and its description is as follows:

$$\text{Max } [\text{Exp}(Z)(x)] + \phi^{*}\text{Var}[Z(x)]$$

subject to,

$$\begin{array}{lll} (a_{ij})_k(X_j)_k & \leq U_{ij}b_i & (i= 1,2...m) \\ \text{Prob } (Ax \leq b) & \geq e & \\ \Sigma U_{ij} & = 1 & (j= 1,2...n) \\ (X_j)_k & = \phi & (k= 1,2...K) \end{array}$$

where,

ϕ	=	risk aversion constant,
$(a_{ij})_k$	=	value of a_{ij} in the k-th probabilistic environment,
U_{ij}	=	allocating factor for the i-th resource,
e	=	m * 1 vector of probability levels.

Discrete stochastic programming uses linear segmentation to approximate the decision-maker's utility function. Rae (1971a, p. 452) states that in using a convex function there is an accepted assumption of constant absolute risk aversion, while by approximating such a function with a number of linear segments the convexity assumption of linear programming holds good. Should the utility function be nonconvex, it may still be approximated with a number of linear segments and incorporated into a linear programming model. This statement of Rae's (1971a, p. 452) is found in Hadley (1964) and supported also by Hazell and Norton (1968), solving non-linear problems, when separated linear algorithms are available in the programming model.

Discrete stochastic programming is formulated as a programming model with quadratic characteristics, where all the variability in the programming coefficients is transferred to units similar to those of the objective function. Its multidimensional process cannot be used when multiple stochastic enterprises and multiple states of nature are considered.

4.4.4 **Hazell (1971): MOTAD Criterion**

MOTAD is a linear criterion to approximate E-V analysis and was initially proposed by Hazell (1971). Operationally, it differs from E-V analysis in that instead of considering expected income variance V(Y) values it uses total absolute deviations $|Y_i - \mu|$ of the income set. In this way risky options can be linearly described by the combination of expected income E(Y) and their mean absolute deviations $|Y_i - \mu|$. With MOTAD, linear estimators of income dispersion $(Y_i - \mu)$

can replace the variance V(Y) of the quadratic algorithm. Such a model generates farm plans with a defined set of incomes of minimised absolute deviation (Hazell 1971; Anderson *et al.* 1977; Tauer 1983; King and Robison 1984; Barry 1984; Hazell and Norton 1986; Parton 1989).

Statistically, the mean absolute deviation is defined as,

$$M = \Sigma \mid Y_i - \mu \mid /n$$

where

M	=	mean of the total absolute deviations
n	=	size of set of income values
Y_i	=	1, 2, 3 ...i values of the income set
μ	=	average income or expected value of the outcome variable

At the time MOTAD was developed, the linear approximation to risky problems was considered extremely useful because of the computational difficulties of the quadratic algorithm. Hazell (1971) compared the properties of the quadratic algorithm and the MOTAD algorithm in order to assess the advantage of linear methods. He found that linear computerised models were more easily available, smaller and far less complex. Further, sensitivity information generated by linear programming models was more comprehensive than that generated from the quadratic exercise.

With the MOTAD method, decision makers choose between possible crop and livestock enterprise combinations on the basis of expected net return and the absolute deviation of net return for each enterprise. This is possible since the MOTAD approach takes into account an adequate allowance for covariance between enterprise net returns, by recognising the mutually exclusive nature of the sample vectors of activity revenues, together with their relative frequencies (Hazell and Norton 1986). With MOTAD the risky farm planning problem can be incorporated in a mathematical programming format such that the mean absolute deviation M can be minimised for a given level of expected profit E(Y) varied parametrically over a relevant range. When the distributions being ordered are approximately normal, the MOTAD efficient set closely resembles the E-V frontier (Anderson *et al.* 1977).

In Figure 4.11 it is possible to observe that under the MOTAD formulation an outcome distribution F with mean income value Y_f and mean absolute deviation M_f, dominates an outcome distribution G with mean income value Y_g and mean absolute deviation M_g, if $Y_f > Y_g$, $M_f \leq M_g$ and at least one of the inequalities is strict (King and Robison 1984). MOTAD has no option for ranking of alternative income and absolute deviation distributions beyond a first level of dominance, unlike the stochastic dominance criterion (FSD and SSD), and therefore demonstrates a low discriminatory power. Hardaker, Pandey and Patten (1991) comment that although the E-M frontier approximates the E-V frontier, MOTAD is less stochastically efficient than the latter, and which this means that it is even less likely to contain the utility maximising solution for a given farmer. Though this statement is relevant from a theoretical point of view, from a managerial perspective this is irrelevant, since MOTAD is able to have discriminatory power for a specific situation in the domain of a production function.

MOTAD offers obvious advantages for stochastic planning that have been highlighted by several authors (Anderson *et al.* 1977; Hazell and Norton 1986) as follows:

(a) It uses a linear algorithm to approximate quadratic problems.

(b) It offers similar results to the quadratic algorithm.

(c) Probabilities can be attached to the activity revenue values (Y_i).

Since MOTAD is an approximation of E-V analysis, it can be criticised on the same grounds. It is generally assumed that the MOTAD efficiency criterion

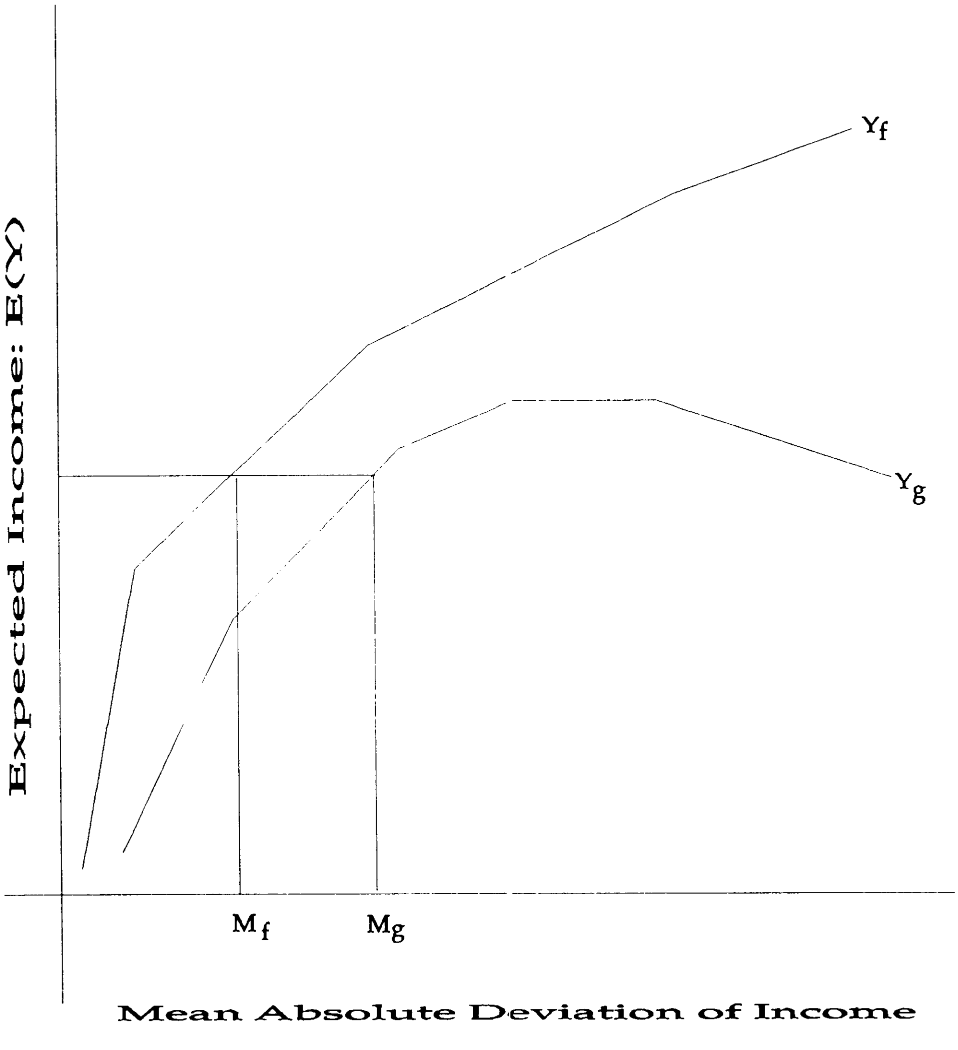

Figure 4.11 MOTAD in Stochastic Farm Planning

holds for risk averse decision makers (King and Robison 1984). With the E-V criterion it is possible to relate to some form of utility function, while with MOTAD this is not possible in a strict sense (Parton 1989, p.40).

4.4.5 **Wicks and Guise (1978): MOTAD with RINOCO**

In general it is assumed that in a non-sequential problem the multivariate joint probability distribution of the elements of the stochastic constraints is discrete. Solutions can be obtained using components of the discrete stochastic programming approach (Cock 1968 and Rae 1971a,b). The option to solve the problem using a game theory approach is envisaged but Wicks and Guise (1978) point out two distinct disadvantages. Firstly, a large number of solutions are required to obtain an acceptable answer to any problem, and secondly only one of these solutions associated with the multiple observations of the multivariate distribution is optimal for the decision maker.

Since these models are solved using discrete stochastic programming, all the variability of the input-output coefficients is transferred directly into the objective function of the model as a straight financial effect, though chance constrains and continuous distributions are used, combined with a MOTAD algorithm, to make the proposal different to those from Cock (1968) and Rae (1971a,b).

The problem is finally solved as a quadratic programming exercise, or as a simple linear programming exercise converting the mean absolute deviations into standard deviations, using a scalar. A value for a linear risk aversion coefficient (ϕ) is arranged and the term ($\phi*\sigma$) is added to the objective function. The proposed model is written as follows:

$$\text{Max } Z = e'Cx - \phi\sigma$$

subject to,

$$EA^*x + Hw \leq b,$$

$$-MCx - I_cY_c \leq \phi,$$

$ge'Y_c - \sigma \quad \leq \phi$

$M^*A^*x - I_cY_c \quad \leq \phi$

$GEY_a - I_mW \quad \leq \phi$

being,

$X \geq 0$; $g \geq 0$; $Y_c \geq 0$; $Y_a \geq 0$; $W \geq 0$,

where,

E is a m*ΣT matrix having T non-zero elements in each row, each taking the value 1/T, these being placed both diagonally,

A is a ΣT*n matrix containing in the first T rows the sample observations on the elements of the first row of the matrix and so on for each on the m sets of coefficients defined in A,

e is a T*1 vector of elements each taking the value (1/T) where T is the sample size of observations in gross margins;

I_c is an identity matrix of order T;

M is $(I_c\text{-}T_{ee'})$ and creates deviations from sample mean values with the matrix C;

Y_c is a T*1 vector containing element representing sums of absolute values of weigthed negative deviations from sample mean gross margins;

g is an m * m diagonal matrix with elements g_{ii}. The g_{ii} transforms mean deviations into standard deviations;

Y_a is a ΣT_i*1 vector containaing elements representing absolute sums of weighted positive deviations of input-output coefficients from their sample means;

w is an m*1 vector of estimated standard deviations for requirements of each resource, and

H is a m*m diagonal matrix of risk aversion coefficients associated with the individual resource constraints, these reflecting the permissible probability of each particular constraint being violated.

4.4.6 **Tauer (1983): Target MOTAD**

Target MOTAD is a stochastic planning criterion proposed by Tauer (1983) and based on Hazell's (1971) statements.

Target MOTAD belongs to the group of safety-first models that have a different perspective in behavioural terms. Risk is represented by the chance of loss in safety-first models. Chance of loss can be viewed as the probability of income falling below a critical target level defined by subjective perceptions or analysis of historical performance of the system. The size of loss is measured as absolute deviations below the target level. This target level may be included in programming models as an additional constraint to the system (T). Bertelsen (1985) summarises the behavioural models of Tesser, Kataoka and Ray which consider the probability of loss within the decision model. Parton and Cummins (1990) and Fleisher (1990) label this chance of loss as downside risk.

Safety-first models are most appropriate where the risk of catastrophe is large, either because of an inherently risky environment, or because the farmer has not allocated reserves to fall back on in a bad year (King and Robison 1984). The criterion calls for selection of the farm plan that minimises the probability that income Y_t could fall below Y_0, that is, the decision maker should choose the plan for which $P(Y_1 < Y_0)$ is minimum where Y_0 is the target value to be achieved.

Low (1974) proposed an initial safety-first model that selects the farm plan that has an income equal to or greater than Y_0 in every state of nature, and which maximises expected income E(Y). The model will produce a standard linear programming solution for maximum E(Y) if Y_0 is sufficiently small that none of the constraints in the new restriction are binding (Hazell and Norton 1986). This general mathematical formulation is as follows:

$$\text{Max } E(Y) \quad = \quad \Sigma\, c_i\, X_j$$

subject to,

$$\Sigma\ c_i\ X_j \quad \geq \quad Y_o; \quad \text{(new restriction)}$$

and

$$\Sigma\ a_i\ X_j \quad \leq \quad b_i; \quad \text{for all } i$$

$$X_j \quad \geq \quad 0; \quad \text{for all } j$$

where,

$E(Y)$ = expected income;

c_i = income per farm-activity unit;

Y_o = target boundary income;

X_j = level of production of the j-th farm activity;

b_i = level of resource or constraint i-th.

A difficulty with this model is that there may not be a feasible solution if Y_o is large relative to the maximum attainable expected value of the objective function, and the farmer is operating in a highly risky environment (Hazell and Norton 1986). Tauer (1983) overcame this constraint by developing the Target MOTAD criterion with important differences when compared with Hazell's algorithm:

(a) It is concerned with increasing a farmer's utility by minimising an appropriate measure of the variability of farm income within the assumptions of a safety-first specification.

(b) It is a two-attribute, risk and return model where return is measured as the sum of the expected returns of activities multiplied by their individual activity level risk; and risk is measured as the expected sum of the negative deviations of the solution results from a target-return level.

(c) The Target MOTAD formulation generates an efficient set of solutions for a given target T value of the objective variable. Target MOTAD will never choose a dominated plan, regardless of the target selected. A plan is dominated if another plan exists which has a higher income in every situation or year (Watts, Held and Helmes 1984).

(d) Hardaker *et al.* (1991) confirmed findings by Tauer (1983), Porter (1974) and Fishburn (1977) that Target MOTAD solutions are second degree stochastically dominant, meaning that they are stochastically efficient for risk averse farm decision makers. Since stochastic dominance is based on the expected utility theory, these results indicate that Target MOTAD is consistent with decision theory. The proof that Target MOTAD is second-degree stochastic dominant is illustrated by Tauer (1983).

(e) Target MOTAD maximises mean income subject to a limit on the total negative deviations measured from a fixed target value rather than from the mean. Since deviations are not measured from the mean, but from the target, total negative deviations do not necessarily equal the total positive deviations (Kramer 1990, Tauer 1983).

(f) Target MOTAD allows for comparison between solutions using a common risk preference point while in MOTAD the risk preference point is equal to and moves with the mean.

(g) Safety-first models penalise negative skewness in the distribution. A risk averse individual would prefer a positively skewed distribution to a negatively skewed distribution with the same mean and variance (Bertelsen 1985). A distribution of returns with more observations in the lower tail would have more returns below target, i.e. more risk.

Tauer (1983) mathematically represented the Target MOTAD model as follows:

$$\text{Max } E(Z) = \Sigma\, c_i\, X_j \qquad \text{(Equation 1)}$$

subject to:

$$\Sigma\, a_i\, X_j \leq b_i \qquad \text{(Equation 2)}$$

$$\Sigma\, c_{is}\, X_j + Y_n \geq T \qquad \text{(Equation 3)}$$

$$\Sigma\, p_n Y_n \quad = \quad \lambda \qquad \text{(Equation 4)}$$

$$X_j \quad \geq \quad 0 \qquad \text{(Equation 5)}$$

where

$E(Z)$ = expected return of the farm system;

c_i = expected return i-th of the activity j-th;

X_j = level of the activity j-th;

a_i = technical requirement of the constraint i-th for activity j-th

b_i = level of resource or constraint i-th;

T = target level of return;

c_{is} = return of the activity j-th for state of nature s;

Y_n = deviation below target for state of nature n;

λ = constant parameterised from 1 to 0.

p_n = probability that observation n will occur;

n = number of activities; and

s = number of states of nature.

4.4.7 Lambert and McCarl (1985): Direct Solution of Nonlinear Approximations of the Utility Function

After criticisms of E-V analysis, Lambert and McCarl (1985, pp.846) focused the controversy on the development of a solvable expected utility maximisation model which is free of restrictions on the forms of the utility function, particularly those regarding the sign of the risk aversion parameter, and free of assumptions regarding the distribution of the uncertain parameters. The initial model by Lambert and McCarl (1985, pp. 847) seems to be the reference point for new developments in stochastic programming, where different risk attitudes of the decision maker can be incorporated in the objective function domain without requiring the assumption of normally distributed returns (Patten *et al.* 1988, p.90).

The mathematical specification of Lambert and McCarl's algorithm is as follows:

Max E(U)	=	$\Sigma\ p_k\ U(Z_k)$
subject to		
$a_i\ X_j$	$\leq$	b_i
$c_k\ X_j - Z_k$	=	$-Z_o$, k = 1, 2, ... n
X_j	$\geq$	0
R_k	$\geq$	0
where		
U( )	=	a monotonic quasi-concave utility function that permits risk aversion and risk preference in its domain
Z_k	=	a vector of returns by state (k = 1, 2, ... n)

The maximisation of this formulation leads to a global maximum where the objective function is quasi-concave. This condition allows for points in the function where the decision maker may exhibit a risk averse behaviour, but also has domains for decreasing risk aversion behaviour (Patten *et al.* 1988). Importantly the absence of restrictions on the underlying distributions of the utility functions and the multiple specifications of the risk attitude of the decision maker with respect to changing levels of wealth are important aspects that make the algorithm attractive in managerial decision-making.

Lambert and McCarl (1985) offers as desirable that their proposal is free of restrictions on the form of the utility function (it needs to only be quasi-concave), an assumption reinforced by Patten *et al.* (1988) and Pannell (1988). Furthermore it is free of assumptions regarding the distribution of uncertain parameters (Pannell 1988). However, Hardaker *et al.* (1991) criticise this approach as impossible or inappropriate because it requires the individual farmer's utility U( ) be elicited for direct incorporation into a utility maximising risk programming model, making the exercise rather theoretical.

4.4.8 **Okunev and Dillon (1988): Mean-Gini Criterion**

The Gini's mean-difference proposed by Yitzhaki (1982) was implemented in the context of optimal farm planning by Okunev and Dillon (1988) in situations where full knowledge of the decision-maker's utility function is lacking, for an absolute risk averse utility-maximising farmer. The Gini's mean-difference is simply the expected absolute difference between all possible pairs of observations of a random variable. An efficient set may be identified using the probability distribution of returns for one or more farm plans and applying mean-Gini efficiency conditions (Yitzhaki 1982, p. 181).

Mean-Gini criterion can only be implemented under an assumption of a continuous probability distribution of returns, though in operational terms discrete return values are used within a framework of linear segmentation. The approach is criticised on the same grounds of E-V and SSD criteria.

4.4.9 **Patten, Hardaker and Pannell (1988): Utility Efficient Criterion**

The utility efficient programming (UEP) criterion, proposed by Patten *et al.* (1988) and Hardaker *et al.* (1991), integrates components of Lambert and McCarl's (1985) algorithms as a means of generating a set of solutions of wider interest when less than complete information is available about the farmer's risk attitude. The objective function is the parametric sum of two parts of the utility function in which the degree of risk aversion varies systematically with the decision maker's objective function. This involves approximating the utility function with linear segments. Each linear segment requires an activity U_i, and the function as a whole requires an extra constraint, I. The coefficient of each U_i in constraint C is the wealth value at one of the corner points and the objective function is the corresponding utility value. The constraint I limits selection of U_i activities such that utility lies on or below the linearly segmented utility function (Jones 1994). Patten *et al.* (1988) state that the technique has several advantages over others previously available:

(a) A number of different types of utility functions are applicable including ones exhibiting decreasing risk aversion.

(b) The degree of risk aversion can be limited to a plausible range; this means that all knowledge about the range of risk aversion relevant to a particular farmer can be easily incorporated into the model.

(c) The form of the distribution of activity revenues is flexible; therefore, no assumption of normality is required.

(d) The technique can be incorporated within the currently available mathematical programming software.

There is a common element between proposals by Lambert and McCarl (1985), Patten *et al.* (1988) and Hardaker *et al.* (1991) which is the need to generate a maximising algorithm where the domain of the utility function can change with the risk attitude of the decision maker. Therefore, Patten *et al.* (1988) reformulate the proposal by Lambert and McCarl (1985) in order to generate an expected utility maximising criterion without constraints on available utility function shapes or elicitation of farmer's utility function, using parametric objective programming. Hardaker *et al.* (1991) propose the definition of a separable utility function of the form,

$$U(Z) = G(Z) + \lambda H(Z)$$

where variation in the parameter λ can be interpreted as variation in risk preference. G and H are appropriate selected functions of Z. Another component of this proposal is a "sumex" function of the form:

$$U = -\exp^{(-az)} - \lambda\exp^{(-bz)}, \quad a,b,z > 0$$

Therefore the re-adjustment to the original UEP criterion putting forward the negative exponential utility function as more suitable is as follows:

$U(Z)$	=	$\exp[- \{(1-\beta)g + \beta h\}z]$;
		β is parametric.

The UEP programming model may be written as,

Max $E(U)$	=	$\sum p_k [G(Z_k) + \lambda H(Z_k)]$
subject to		
$a_i X_j$	$\leq$	b_i
$-c_k X_j + I_{zk}$	=	0
$p_k I_{zk}$	$\leq$	1.00
X_j	$\geq$	0
where		
λ	=	non negative parameter that varies using a parametric programming algorithm. At each change of basis, corresponding to a particular level of risk aversion, the E-V solution is identified. When $\lambda = 0$ the r_a (coefficient of risk aversion) = a, whereas when $\lambda \rightarrow \infty$, the $r_a \rightarrow b$;
p_k	=	probability of state k;
G & H	=	two points in the utility function;
Z_k	=	total revenue for state k; (k = 1, 2, ... n);
C_k	=	activity revenue vector for state k_n; c_k values represent the uncertainty in activity revenues. Therefore, there is not need to assume any standard form of distribution. Suitable values may be observations from previous years or cross-sectional data, which can be treated as a sample of equally likely outcomes or as states with subjectively assessed probabilities;
X_j	=	vector of activity levels;
a_{ij}	=	matrix of input-output coefficients;
b_i	=	RHS coefficients;

I_{zk} = identity transferring matrix (q by 1 vector) of weights representing each of the q segments of G and H for each state k.

The sumex function has the desirable property that the function exhibits decreasing absolute risk aversion with increases in return (Z) because of the effect of (Z) in the exponential algorithm. Moreover, as the parameter λ is varied, the coefficient of absolute risk aversion varies between a and b. The coefficient of risk aversion (r) is defined as the elasticity of the marginal utility of return by Patten *et al.* (1988, p. 9). Bardsley and Harris (1987) use a constant absolute risk aversion coefficient of 0.00006. However this coefficient may vary from values of 0.00001, for a risk neutral decision maker, to 0.001, for an extreme risk aversion decision maker (Jones 1994, p.20).

Jones' (1994) review of different available approaches to risk management in programming models states that utility efficient models can use a range of utility functions. Two examples are given below with the first function having constant relative risk aversion and decreasing absolute risk aversion, while the latter functional form has a constant absolute risk aversion:

$$U = a + bW^{(1-r)} \qquad \text{(Equation 1)}$$

$$U = 1 - e^{-AW} \qquad \text{(Equation 2)}$$

where U is a utility function, a and b are constants, W is wealth, r is the constant relative risk aversion coefficient and A is the constant absolute risk aversion coefficient.

4.4.10 Pannell (1988): Direct Expected Utility Maximising Linear Programming (DEMP).

DEMP is proposed by Pannell (1988) and supported in the theoretical elaborations of Lambert and McCarl (1985) except that it requires a concave utility function to be solved as a segmented linear programming exercise. When requiring a function domain of concave shape the increasing absolute risk aversion of the decision maker is accepted as a tolerable restriction within this proposal.

DEMP implies an elicitation of the farmer's utility function (U) and REQUIRES specific values of U for specific segments of the function to be worked out (i.e. several utility levels for the wealth levels used). The adoption of a linearly segmented utility function may represent increasing, constant or decreasing risk aversion and non assumptions about the underlying distributions of revenues is required (Pannell 1988).

Pannell (1988) offers his model as an alternative solution to MOTAD with the advantage of better approximation to the traditional theory of risk (i.e. expected utility maximisation) and the opportunity of solving linear programming problems with minimal introduced error.

4.4.11 **Pope and Just (1991): Constant Relative Risk Aversion (CRRA)**

Pope and Just (1991) support their discussion on the assumed evidence that risk aversion is a normal component of the decision making process, but whether risk aversion is constant, decreasing or increasing remains ambiguous, with decreasing absolute risk aversion emerging as a "stylised" fact or belief. Econometric models were used to test multiple hypotheses, each representing different attitudes to risk from the decision maker.

These authors based their arguments on empirical exercises in a potato farming environment and found strong evidence to test the hypotheses of risk neutrality, constant absolute risk aversion and constant partial relative risk aversion of the decision maker and their influence in "farm wealth" and "farm profit". The data lent weight to the hypothesis that these type of farmers exhibit a constant relative risk aversion and that relative risk aversion behaviour can be incorporated within a single equation in programming models introducing wealth (W), with W being essentially linear in nature in the firm's supply analysis (Pope and Just 1991, pp. 743, 744, 747).

The concept of "constant relative risk aversion" is supported in Pratt (1964) and Arrow (1971) and in Menezes and Hansen (1970) as stated by Pope and Just (1991).

Just and Pope (1991) argue that any analysis which only uses profit as the argument of utility is inappropriate since profit can be negative and the stochastic effect of the decision maker's attitude can not be perceived. The possibility of negative profit merely imposes restrictions in overall U. Evidently absolute or relative risk aversion yield similar risk-preferring behaviour in the region of negative profit.

When evaluating the Target MOTAD criterion it was specified that only positive returns from the farm enterprises considered stochastic would enable the effect of the random events in farm performance (i.e. enterprises considered affected by technical risks) to be seen through stochastic input-output coefficients. For the particular case of CRRA the algorithm is considered valuable for setting the independent effect that the decision maker's attitude may have on farm profit and wealth in the objective function of a programming model incorporating wealth.

Under the specific conditions of the case-study (i.e. potato farming), Pope and Just (1991, p. 746-747) found reason to reject the hypothesis of risk neutrality. Similarly, constant absolute risk aversion is rejected in favour of non-constant absolute risk aversion. There was no strong evidence to reject a constant relative risk aversion attitude (C.L.= 89.12 per cent). The authors supported their findings with the intuitive arguments of Arrow (1971), favouring CRRA in stochastic planning models, to include the stochastic influence of the decision maker in final farm performance.

4.5 Holistic Stochastic Modelling for this Farming System

This study outlines a procedure to incorporate the instability of the farm system in a decision planning model by defining, in an holistic manner, stochastic criteria which might manage risk in the farm system. Both the technical components and attitudinal components of risk must be handled in this procedure.

The first step in the procedure was to produce a series of conceptual maps that provide an overview of the changing nature of farming systems. Next, in order to seek theoretical support for the exercise, various criteria for decision making under risk were synthesised to examine how to account for system variability in optimal decision planning models.

This procedure was developed against the background of currently available analytical techniques, and considers managerial purposes. No further mathematical elaboration of the stochastic decision criteria is undertaken in this study: instead it places existing algorithms for on-farm decision-making applications into a managerial framework with soft systems implications.

4.5.1 Conceptual mapping of risk in the farm system

Stochastic elements in the farm system analysis have been identified through conceptual mapping (i.e. see figures 2.1, 2.2, 4.3, 4.4 and 4.5). The views of risk defined in the conceptual maps in Figure 4.3, 4.4 and 4.5 show the wide array of possible contributors to farm system instability. Figure 4.3 defines the link between instability in farm resource allocation and management and environmental (i.e. ecological) risk, financial risk, market risk, decision-maker risk, production risk and technology risk. Figure 4.4 reveals the instability created by focussing the purpose of the farm system on farm enterprises as the system's resources: the related processes as mapped are then the minimisation of threats and maximisation of opportunities for the environmental, technological and management components of the farm system. Figure 4.5 defines instability in the farming system as a consequence of the human influence conditioned by personal factors, social environment, cultural environment, social paradigms, information access and managerial capacity.

Figure 4.12 summarises the multiple sources of risk derived from this conceptual mapping exercise of instability in a farming system. By drawing out the internal dynamics of the farm operation, Figure 4.12 demonstrates that technical risks are independent of the attitudinal risks which derive from managerial influence. Since technical risk deals with operational components, this type of risk is usually considered to be the most important, from a managerial point of view: but attitudinal risk, which derives from how well the decision maker copes with the changeable nature of the system and adjusts the system according to feedback, is a well recognised influence on farming system performance.

4.5.2 Outline of an holistic stochastic planning approach to be applied in this study

The analysis of the available quantitative criteria for incorporating risk in programming models, as outlined previously, shows that each of the different proposals work on the central assumption that all stochastic factors of the system operation are considered, indirectly, through financial scenarios. Although several different methods of stochastic analysis using input-output coefficients are proposed, where strictly technical elements can be managed as such, all of the approaches reviewed offer the same method of incorporating stochastic effects in the functioning of a system, a method based on financial returns.

This limitation is a major constraint when stochastic elements which are not primarily financial in nature have to be incorporated in managerial planning models. A narrow transformation of any ecological aspects, production and management processes which are not amenable to representation in financial terms makes the stochastic exercise rather artificial. To represent only indirectly, through financial terms, technical variables which are not in themselves financial, diminishes the inductive capabilities of the modelling procedures, and reinforces the role of financial or hard system components at the expense of 'soft' management components. None of the following authors offer a solution for technical risk management under the conditions established above: Pratt (1964), Fishburn (1964), Hazell (1971), Tauer (1983), Lambert & McCarl (1985), Okunev & Dillon (1988), Patten *et al.* (1988), nor Pannell (1988). Similarly the applications to risk management in the input:output coefficients of programming models, which Cock (1968), Rae (1971a,b) and Wicks & Guise (1978) report, also follow the traditional approach of converting all the stochastic system into financial measures which affect the objective function directly, and neglect the direct representation of technical components in the programming matrix.

Therefore, the established procedure for the setting of risk components within the programming framework of this study implies a process of adaptation and integration of components from the different available decision criteria, in order to set an holistic stochastic modelling criterion considered suitable for the management focus of this study. The adopted procedure took into account the following considerations:

(a) MOTAD with RINOCO, (Wicks and Guise 1978), showed that the *stochastic elements of the farming system can be managed in a bimodal manner*, firstly, through the input-output coefficients, and secondly, through the objective function. Furthermore it envisages the possibility of exploring the inclusion of more than one aspect of risk within the farm planning context. These aspects were relevant when exploring the possibility of integrating hard and soft system components within a single modelling framework avoiding artificially confining the whole-system variability to exclusively financial performance in the programming model and allowing for a separate handling of the technical and attitudinal risks.

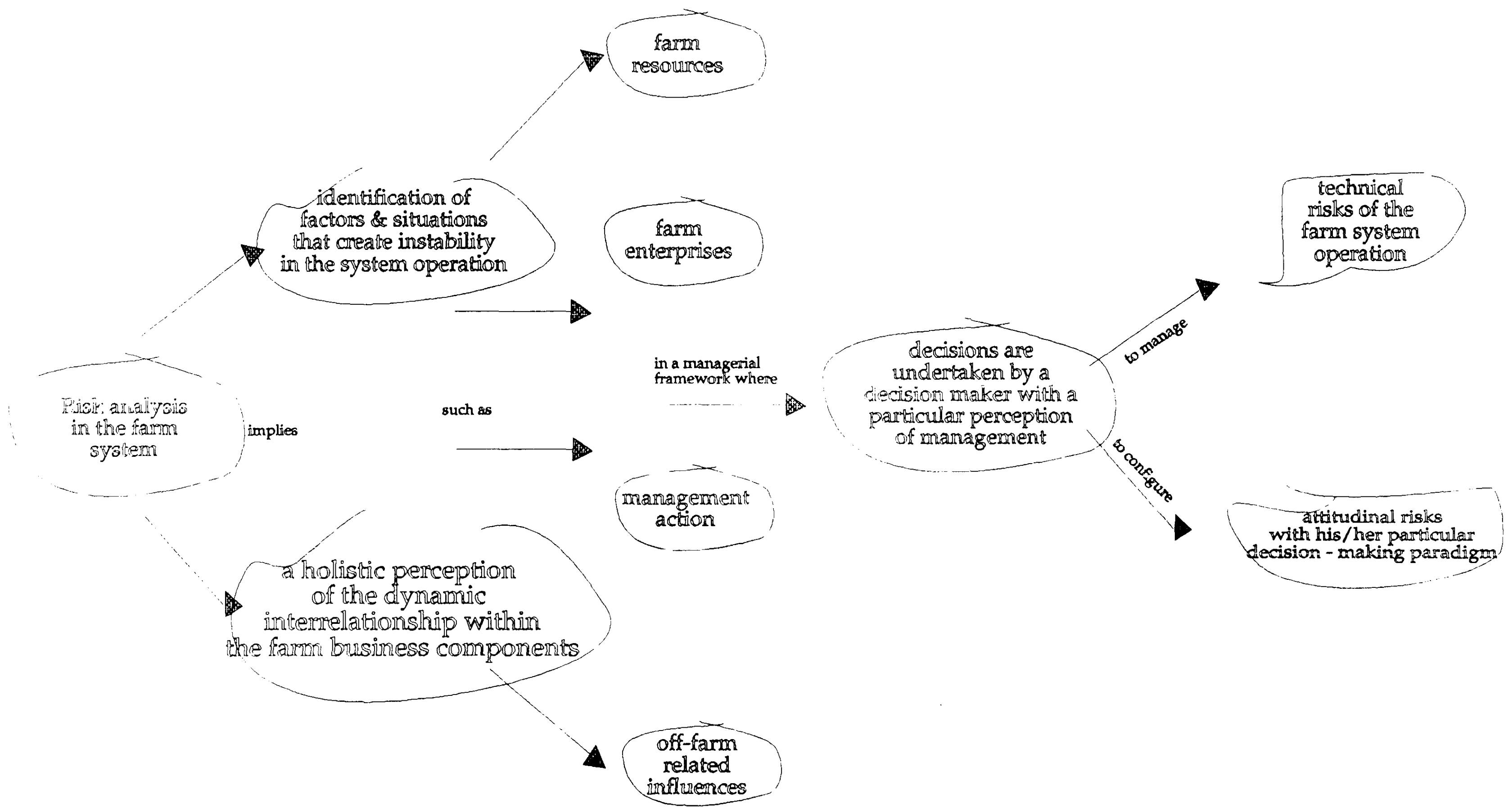

Figure 4.12 A Conceptual Map of Risk in the Farming System

(b) Discrete Stochastic Programming, (Cock 1968, Rae 1971a,b), developed the possibility of using a *probabilistic distribution of random events* as a functional method to incorporate system variability. Integrating this proposal with suggestions from Wicks and Guise (1978, p.38; i.e. the consideration of more than one aspect of risk), critical variables of the farming system may be identified and their probability distributions worked out. It should be noted that all the *technical* management variables are likely to be considered.

There is no apparent practical constraint to setting as many stochastic variables as needed in the input-output coefficients of the model. Therefore, the density functions may be arranged not only for financial effects but also for ecological and biological aspects of the system operation. For example, in the case-study farm where the farmer identified lambing rate as a critical factor to farm performance, an historical data set of lambing rates was organised from farm records. A relative frequency distribution approach was used to generate the related probability distribution of lambing rate values and the stochastic effect refers exclusively to ewes' reproductive performance within the model.

The set of performance vectors (one for each state of nature) for the probability distribution of the random events is used to represent the technical variability of the farm system operation. These values may be actual observations from historical data, or they may be subjectively determined. When historical data is used the probability of each state of nature follows a relative frequency distribution approach (i.e. n_i/n). If a subjective approach is used a probability distribution function of weighted values per state of nature may be organised.

(c) Target MOTAD, (Tauer 1983), involves establishing a *target value of reference against which the random events should be screened in order to minimise the negative deviations* that influence farm performance. From a managerial perspective, this aspect represents a clear rational attitude from the decision-maker's side. In a farm environment, the farmer is only likely to implement activities and/or to continue carrying on enterprises that remain viable above at least minimal parameters of reference (e.g. sheep enterprise with a minimal 75 per cent lambing rate; cow-calf enterprise with minimal 95 per cent calving rate; steer enterprise with a minimal weight of 500 kg at 2 years of age; heifers at first calving with a maximum age of 24 months, etc).

The above descriptions provide the foundation for the setting of stochastic input-output coefficients. While components abstracted from different approaches were used, it can be said that the adopted methodology does not belong to any of the specifically described stochastic decision criteria. The methodology was tailored for the particular purposes of research into the case study, and was focused specifically on managerial characteristics, in an attempt to include the factors that condition technical risk in farm performance, and to retain their influence in the specific technical environment of the programming model.

(d) An initial exponential modification proposed be Hazell and Norton (1986) within the context of simple linear models to include a variable risk attitude of the decision-maker was the trigger: it showed that the *attitudinal risk of a farmer could possibly be incorporated in the model in an independent manner*, at the objective function level. Hazell and Norton (1986) proposed this algorithm as an alternative to fit a different risk attitude than the increasing absolute risk aversion that is assumed by MOTAD.

(e) Lambert and McCarl (1985) criticise the use of quadratic utility functions which imply an increasing risk aversion with increasing wealth and the proposal of quasi-concave utility functions that allow for positions of *variable risk attitude of the decision-maker in specific domains of the* *utility function.* Hazell and Norton (1968) saw that a utility function with an exponential algorithm should be suitable to elucidate the risk-taking perception of the farmer, once the target values of reference in the management of the farm system (i.e. those encompassing the analysis of technical risks) had been achieved. This is why a two-stage holistic risk management process was considered necessary within this analysis. The management processes of the farm resources were defined by Stacey (1983) as choice, action, reaction: this implies a series pf decision processes where the farmer changes his/her view on management and how objectives might be achieved depending on the results of prior decisions and states of nature. When considering the instability of the farm system operation, the decision maker is concerned with aspects that create risk in two ways: those that affect the initial value of the enterprise (i.e. wealth or net worth) and those that affect the profit of the current exercise (i.e. current net returns). With the setting of stochastic input-output coefficients these aspects clearly influence the profit component of the system operation. This means that further consideration of any stochastic effects on farm wealth will stem from the attitude to risk of the decision maker.

(f) Cock (1968), Rae (1971a,b), and lately Patten *et al.* (1988), Pannell (1988), and Hardaker *et al.* (1991) have discussed the use of segmented utility functions to accommodate function domains where the degree of risk aversion varies systematically with the decision-maker's utility function. This discussion, and comparable models where less than complete information is available about the farmer's risk attitude, encouraged the use of an exponential function of linear segmentation in setting attitudinal risk in this study. Jones' (1994) description of different options of utility functions, also supported by Hardaker *et al.* (1991), gave some assurance that a suitable stochastic utility function would be found, which, through a trial and error exercise, could be applied to the case study farm in a simulated programming model. Consideration should also be given to Hays and Winkler's (1970) proposal of exponential functions (i.e $e^{-\lambda T}$), where λ

is the probabilistic factor and T is a constant value of the stochastic event.

(g) Pope and Just (1991) showed that the common assumptions of increasing absolute risk aversion and constant absolute risk aversion are incongruent, and that constant relative risk aversion is better supported in the domain of utility functions. This statement provided final support for the setting of an attitudinal risk objective function as described above. These authors also differentiate stochastic effects in farm profit and in farm wealth, consistent with the assumptions of Lambert and McCarl (1985). These aspects were also considered in setting the stochastic objective function of this study.

If constant relative risk aversion (CRRA) is accepted as per Pope and Just (1991), the effect of attitudinal risk in the objective function can be constrained to the wealth component of the financial farm value (i.e.W_0). Jones' (1991) described function, that encompasses domains for constant relative risk aversion, may then be used. The selected function may be linearly defined for farm profit and farm net worth (i.e. W_0). Farm profit bears the stochastic effect of technical risks and farm wealth (i.e. net worth) carries the stochastic effect of attitudinal risk.

As supported in Pope and Just's (1991) findings about the importance of wealth (i.e. net worth) for a real indication of the decision-maker's attitude to risk in farm business management, the static model of this study incorporates variable wealth (i.e net worth) within the programming model.

A mathematical representation of the overall holistic stochastic modelling criterion of this study may be defined as follows:

$$\text{Max } E(Z) = \Sigma\{(\Sigma a_i X_j + \Sigma \lambda a\, X_j) + W_0^{(1-r)}\} \qquad \text{(Equation 1)}$$

subject to,

$$\Sigma\, a_i\, X_j \leq b_i \qquad \text{(Equation 2)}$$

$$(\Sigma\, c_{is}\, X_j + Y_n) \geq T_1 \qquad \text{(Equation 3)}$$

$$(\Sigma\, a_{is}\, X_j + X_n) \geq T_n \qquad \text{(Equation 4)}$$

$$\Sigma\, p_n Y_n = \lambda \qquad \text{(Equation 5)}$$

$$\Sigma\, p_n Y_n = \lambda \qquad \text{(Equation 6)}$$

$$X_j \geq 0 \qquad \text{(Equation 7)}$$

where

$E(Z)$	=	expected return of the farm system;
λ	=	probabilistic effect (i.e technical risk) of random enterprises with stochastic input-output coefficients; constant parameterised from 0 to 1;
$(1-r)$	=	exponential effect of the decision-maker's risk attitude with variable coefficient of risk aversion (r);
W_0	=	initial wealth (i.e. net worth);
c_i	=	expected return i-th of the activity j-th;
X_j	=	level of the activity j-th;
a_i	=	technical requirement of the constraint i-th for activity j-th;
b_i	=	level of resource or constraint i-th;
T_l	=	target level of financial input variables;
T_n	=	target level for other technical stochastic input variables;
c_{is}	=	return of the activity j-th for state of nature s;
$(\Sigma\, c_{is}\, X_j - Y_n) \geq T$	=	Target constraint for financial variables;
$(\Sigma\, a_{is}\, X_j - X_n) \geq T$	=	Target constraint for other technical variables;
Y_n	=	deviation below target for financial state of nature n;
X_n	=	deviation below target for other non-financial state of nature n;
p_n	=	probability that observation n will occur;
n	=	number of activities; and
s	=	number of states of nature.

r = variable coefficient of risk aversion;

Figure 4.13 shows an overview of risk management in farming systems with different function domains of risk and within the context of quasi-concave functions as implemented in this study.

4.6 Summary

A basic understanding of the theory of risk is a necessary prerequisite to developing a procedure consistent with the broader dimensions of holistic analysis.

Conceptual maps are helpful tools for exploring the practical implications of a system's instability and for defining a framework for risk analysis and management.

There are several recognised methods for incorporating risk in decision models, whose individual limitations can be identified. Each method presents some constraint which prevents it from being applied to the purposes of this study.

If it is generally accepted now that absolute risk aversion decreases (Pope and June 1991, p. 743), it is evidently desirable to use a planning model that takes this into account. In general, farmers show a constant relative risk aversion behaviour of different degrees, depending the point in the domain of their objective functions where they are positioned. Before a point where targets of ecological, technical, financial and management nature have to be achieved it is expected a constant absolute risk aversion represented in the domain of concave functions. Within this boundary the technical effects of the farm system are managed using a stochastic approach of input-output coefficients that are screened through technical parameters of reference using a target algorithm for every input variable considered stochastic.

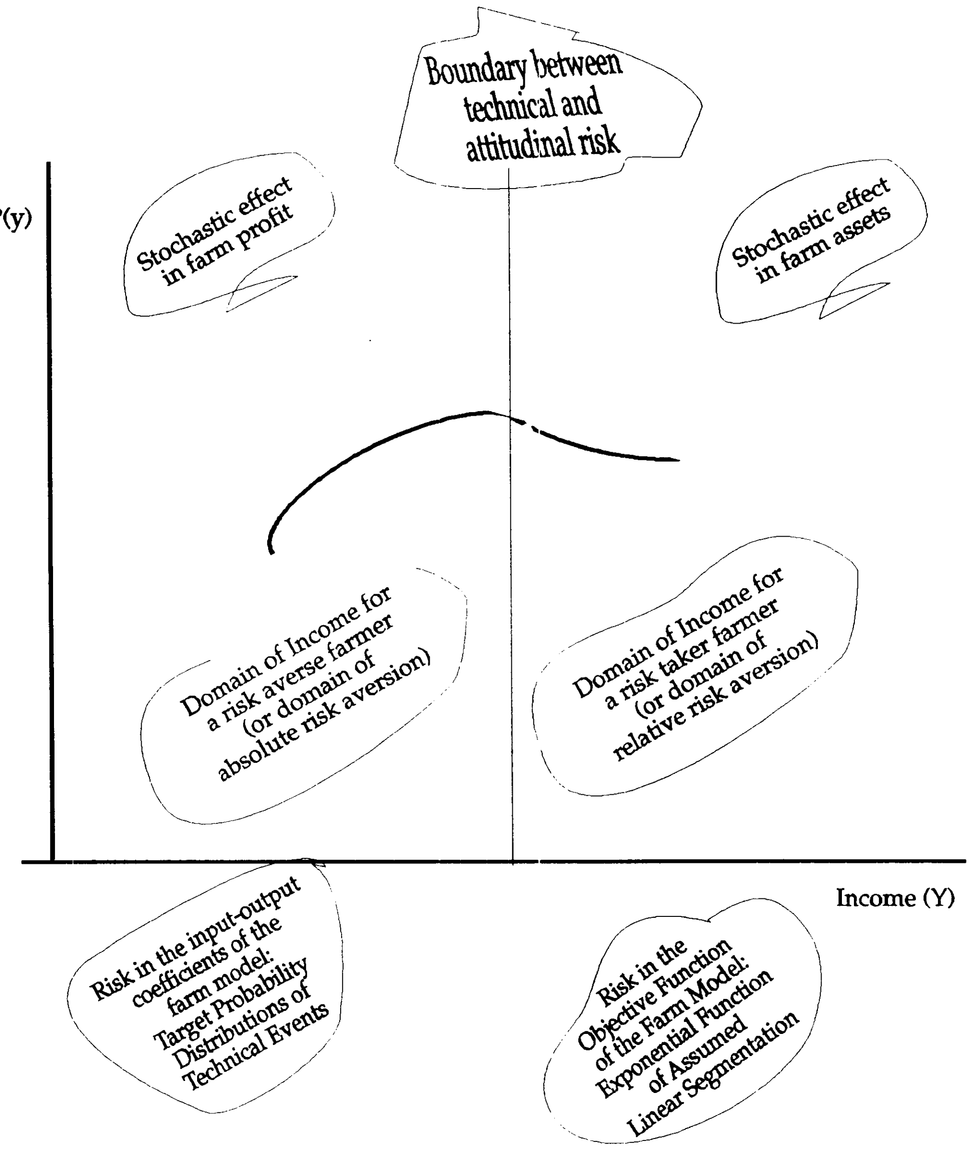

Figure 4.13 Domains of Risk Analysis in Holistic Stochastic Modelling (HSM)

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Afterwards, the holistic model of this study transfers the stochastic effect to the objective function, and mainly to its effect on wealth, since the stochastic effect in the input-output coefficients is considered to affect farm profit. It is difficult to argue that the boundary between the two risk domains (i.e. technical risk and attitudinal risk) obeys exclusively financial dictates. Financial gain is not the only reason for doing farming, and there is more than one argument which would show that farming exists in the inter-relationships amongst soft and hard systems components. Therefore, only an holistic perception of risk management that gives a comparable value to each stochastic variable can inform a meaningful decision making exercise. This study integrates an holistic stochastic method within these guidelines.

While MOTAD and Target MOTAD analyses increase the farmer's utility by minimising some measure of the variability of exclusive farm income, in HSM the minimisation of the variability below a target is not restricted to income but extends to operational variables that encompass the overall definition of technical risk. This whole set of variables represents a management environment and pictures risk without bias.

The stochastic efficiency criterion traditionally included in a monotonically constant objective function is incorporated in HSM to interpret the risk attitude of the decision maker above a point where negative deviations for technical variables have been minimised related to target values. Therefore the decision maker is likely to have a constant relative risk aversion (CRRA) in some segment of his/her utility function represented by an exponential factor encompassing this attitudinal effect in the overall farm model performance.

Chapter 5

THE ANALYTICAL STRUCTURE OF THE WHOLE-FARM MODEL

5.1 Introduction

Chapter 4 outlined the desirable features of a quantitative model able to integrate the whole set of risk management possibilities for farm planning purposes, using a technical and attitudinal framework to risk analysis and management. This chapter will undertake the integration of the above proposed holistic risk management setting within the structure of a prescriptive planning model aiming to improve the holistic perception of systems appraisal.

Approaches to the appraisal of farming systems may range from intuition to analysis, via models of varying degrees of realism and complexity. All of them encompass situations where decisions are made to allocate resources among many possibilities to maximise the decision maker's utility. This is called portfolio analysis by Anderson et al.

(1977) and whole-farm planning can be seen as one such application. Whole-farm planning is one way to improve the efficiency of farm resource use. Dillon (1976) states that efficiency can only be defined in reference to goals and it presumes that gross benefits exceed gross costs. In many situations non-monetary goals will be relevant and inputs will often involve non-priced activities. As a result, efficiency may sometimes be a matter of judgement.

Following Dillon and Hardaker (1980), Gryseels (1988) and Antony and Hardaker (1991), one can classify the techniques for whole-farm planning under the headings of descriptive models and optimising models. Budgeting belongs to the former group whilst mathematical programming belongs to the latter and both are components of the set of prescriptive models.

Prescriptive models may have great power as tools for developing an understanding of the underlying dynamics of the system under review. This is why it is very important to integrate them with inductive modelling since this will produce a better understanding of the system, leading to better management.

Farm budgeting is a technique to show the anticipated consequences of changes in farm methods or organisation in terms of selected measures of performance. Budgets may be constructed on a whole-farm basis or for a particular section of the farming system. The main advantage of budgeting is that it is flexible and simple (Dillon and Hardaker 1980; Gryseels 1988).

Anderson and Hardaker (1979) argue that budgeting is the most adaptable technique for whole-farm planning. Disadvantages of budgeting relate to the lack of any formal optimisation algorithm and the difficulty of taking uncertainty into account. Because the optimality (or near optimality) of any budgeting plan cannot be guaranteed, the analysis must proceed on a trial-and-error basis. It is possible to extend budgeting methods to incorporate risk in the farm system, but this adds complexity to the exercise.

Antony and Hardaker (1991) comment that modelling limitations in budgeting arise less from the technique itself than from the capacity, conceptualising power, creativity, and diligence of the analyst. Modern computer software, particularly spreadsheet programs, has enhanced the scope and facility of budgeting models.

For FSR, econometric models have long been considered to provide a good means of summarising some of the key relationships in a farming system though they are limited by being highly abstract: they do not identify causality in observed relationships between variables, instead they allow important relationships to be quantified. Their limitation lies in the restricted extent to which estimated relationships can be extrapolated from the analysed situations.

Mathematical programming (MP) provides methods by which the observed relationships among the components of the farm system may be established to varying degrees of complexity and realism, while allowing for alternative specifications of the farmer's objectives. Typically, the analysis is concerned with the performance and viability of alternative farming systems in accordance with the farmer's resources and objectives. These farming systems offer alternative outcomes that are usually specified in terms of the expected financial return and sometimes its associated riskiness. Such an emphasis on the financial aspects as the basis of utility is obviously somewhat unreal. This is what is meant by the concept of "hard system" as argued by Checkland (1988b), Wilson (1984) and Forbes (1988). To varying degrees, farmers are certainly concerned with such non-financial questions as leisure (lifestyle), beliefs, sustainability and security either as prime objectives or as trade-offs to profit. These are some of the components that Checkland (1988a) incorporates into the concept of "soft systems" as an alternative way to identify management problems. Such considerations can be accommodated to some degree within the framework of mathematical programming. At the same time it must be noted that analysis which emphasises the purely financial aspects is able to provide a measure of the financial opportunity cost of pursuing non-financial objectives.

The major problem with various optimisation models is mathematical rigidity and the difficulty of satisfactorily reflecting the complex dynamic and stochastic nature of the farming system (Pandey 1986). However, this may be overcome through the analyst's capacity to define a model that adequately reflects the complexity of the farming system being analysed, even though the success of the analysis may depend on the analyst's own creativity and personal intuition.

This study uses mathematical programming in defining a farm decision making model. This model will be applied to "certain" and "probabilistic" scenarios to test the validity of modelling for decision making purposes through an holistic stochastic framework.

The holistic context must remain all important. The specifics of any MP approach and solutions must be integrated, at least intuitively, within the broader "hard" and "soft" dimensions of the whole system. Conceptual mapping initially provides a valid approach to this holistic context setting process.

5.2 Mathematical Programming: An Overview

Mathematical Programming (MP) is encompassed within the overall definition of Operational Research (OR) as per the description provided in Chapter 1. Information on MP which has been used in defining the quantitative model of this study is presented below.

5.2.1 The Basic Linear Programming Model

Linear programming (LP) came to prominence with the development of the simplex method by George Dantzig (1963). Since then, it has been extensively used and developed so that the broad approach is currently better classified as mathematical programming (MP). Anderson et al. (1977), Barry (1984), Bertelsen (1985), Dent et al. (1986), Hazell and Norton (1986), Kingwell and Pannell (1987), Brooke, Kendrick and Meeraus (1992), and Doster (1995) illustrate and outline applications to the agricultural sector and to agricultural production in particular.

Figure 5.1 shows the basic structure of a MP model where farm resources, constraints to farm operation and farm enterprises are integrated using a simple directional diagram. The interrelationships are defined by arrows that incorporate index numbers. Positive values indicate a transferring situation and negative values indicate an allocation situation. This is an essential algorithm for further development of the overall mathematical model. The ending point of the conceptual model is an immediate purpose of constrained characteristics depending upon the objectives of the analyst. Within this research the quantitative analysis aims to improve information in the financial performance of the system; therefore an objective of financial characteristics has been produced which includes profit and farm wealth. Profit indicates the financial activity of the system within the current period of analysis (to which technical risk effects are applied), and wealth indicates the evolution of farm assets value through the current period of analysis (to which attitudinal risk effects are applied).

The directional diagram of Figure 5.1 can be transferred to a symbolic quantitative MP model and its solution can be specified algebraically as a maximisation of the objective function as follows,

$\text{Max } Z = \sum c_i X_j$ (Equation 1)

subject to

$\sum a_i X_j \leq b_i$; (Equation 2)

$\sum X_j \geq 0$; (Equation 3)

where,

Z	is a financial measure of farm performance;	
c_i	is a n * 1 vector of enterprise profits;	$(i = 1 \dots n)$;
X_j	is a n * 1 vector of activities;	$(j = 1 \dots n)$;
a_i	is a m * 1 matrix of input-output coefficients;	$(i = 1 \dots n)$;
b_i	is a m * 1 vector of available resources i-th;	$(i = 1 \dots n)$;

Equation 1 defines the objective function where Z denotes utility, an ending point of the conceptual farm system of Figure 5.1 (i.e. final farm financial value). X_j is the level of production of the j-th farm activity; cij is the contribution to

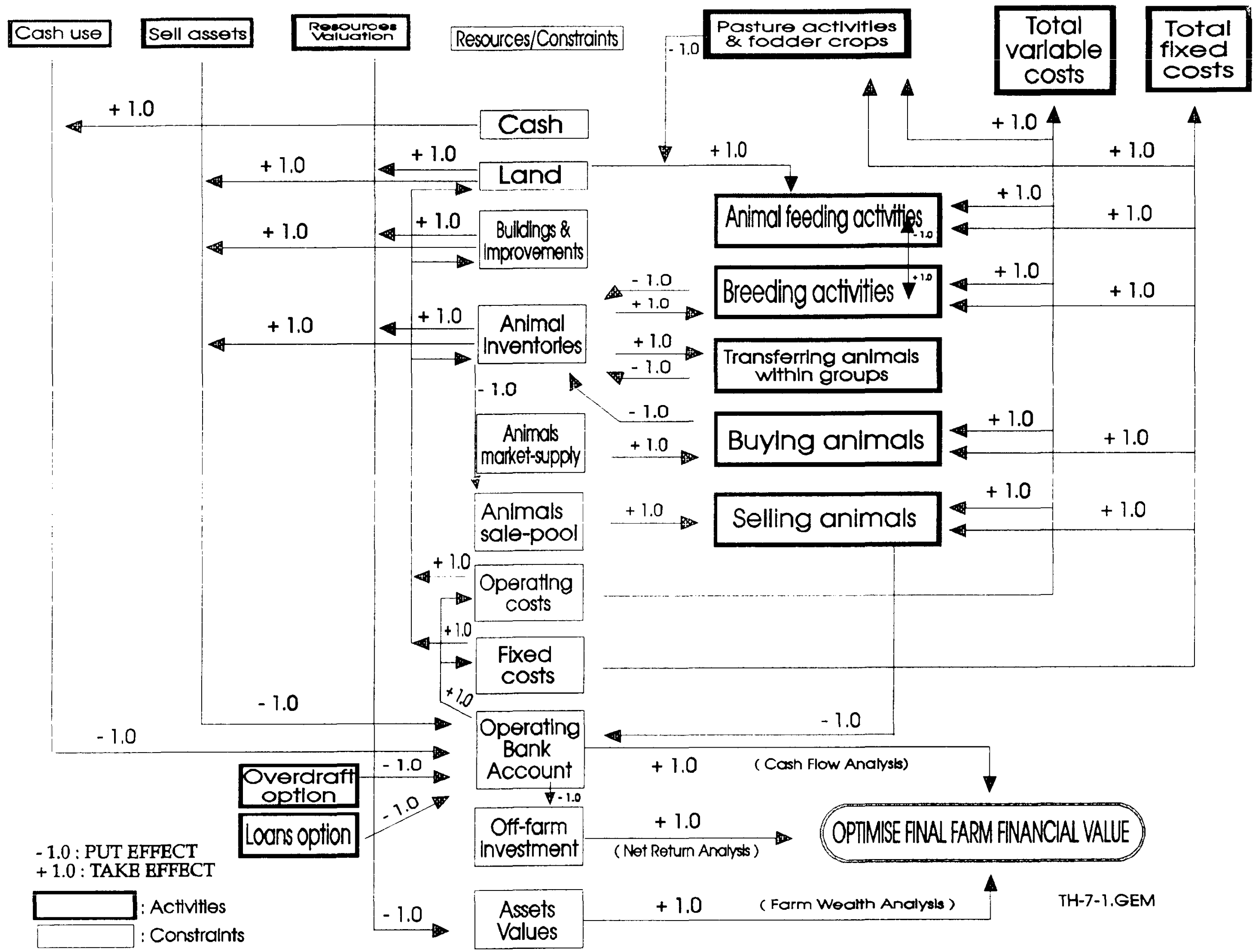


Figure 5.1 Directional Diagram of the Mathematical Programming Model of the Case-study Farm

utility of a unit of production from the j-th farm activity. A farm gross margin objective function considers only the variable costs (C_1) ; a farm net return objective function should consider the variable costs (C_1) and the fixed costs (C_2). Equation 2 defines the resources constraint condition where b_i is the amount of the i-th farm resource available; a_i is the amount of the i-th farm resource required per unit of the j-th farm activity. This equation specifies that no more of the i-th farm resource can be used than is available. Equation 3 specifies that the level of production from any farm activity cannot be negative.

5.2.2 Extensions of the Basic Linear Programming Model

Datzing's basic LP model was criticised on three broad grounds: (a) structure; (b) dynamics, and (c) uncertainty. Modern extensions of the basic model have overcome these shortcomings through such modifications as integer programming to handle resource lumpiness, multiperiod LP to handle resource allocation over a sequence of periods, parametric programming for break-even type analysis, sensitivity analysis and stochastic programming (Lee, Moore and Taylor 1985, Taha 1992). Various forms of linear and non-linear programming options to accommodate risk and non-linearities that may be relevant to the nature of the farm system and the risk attitude of the decision maker have also been developed (Anderson et al. 1977, pp. 189-238).

MP extensions of the basic LP model aim to provide tools in order to deal with its limitations. Several proposals have been implemented and those previously reviewed for the purposes of this study were considered by Cock (1968), Rae (1971a,b), Hazell (1971), Wicks and Guise (1978), Tauer (1983), Lambert and McCarl (1985), Hazell and Norton (1986), Okunev and Dillon (1988), Patten et al. (1988), Pannell (1988), Hardaker et al. (1991) and Parton (1991). These proposals broadly relate to the efficiency criteria for risk management outlined in Chapter 4. Several programming models are offered for stochastic analysis which incorporate the available stochastic criteria at different levels of detail (e.g. Ross 1970; MIDAS: Kingwell 1986, Pannell and Falconer 1986, Kingwell and Pannell 1987; Kristensen 1987; Marz 1989; GAMS World Bank Models: Brooke, Kendrick and Meeraus 1992; and B-95 Purdue University: Doster 1995). The structure of the available

MP models is essentially similar: where differences are found is in the algorithms for management of the variability of the farming system. Because of this, an exercise like this study should not go to available models but instead to examine the sources of the stochastic algorithms as mentioned and analysed in Chapter 4.

Antony (1992) provided an overview of risk-oriented mathematical programming models in the context of farm planning and decision making describing them as follows:

(a) **Models which only incorporate risk relative to the return per activity unit in the objective function.**

These models consider risk in output prices and are referred to as deterministic risk programming, since they contain deterministic constraints. Quadratic risk programming (Lee *et al.* 1985; MOTAD programming: Hazell 1971; Target MOTAD programming: Tauer 1983; Lambert and McCarl 1985; Parton and Cumming 1990; and UEP: Patten *et al.* 1988 and Hardaker *et al.* 1991) are examples of deterministic risk programming.

(b) **Models which incorporate risk in the constraints set.**

This type of modelling is often referred to as stochastic programming since it considers the risky components in the constraint set and RHS. Discrete linear risk programming (Rae 1971); chance-constrained programming (Lee *et al.* 1985); MOTAD with RINOCO (Wicks and Guise 1978); sequential and non-sequential stochastic programming (Anderson *et al.* 1977, p. 215); discrete stochastic programming (Cocks 1968; Rae 1971a); and UEP (Hardaker *et al.* 1991) are some of the available options to account for risk in the constraint set.

5.2.3 A Soft Systems Criticism of Mathematical Programming

There has been a prolonged debate about the practicality of MP (Ackoff, 1973, 1979; Friend and Hickling, 1987; Hopwood, 1980; Checkland 1981; Rosenhead, 1989a;

and Sandberg, 1976). The 'myth' of MP has been one of the major problems of the technique. Critics of the technique call it the 'hard system paradigm' (Checkland 1983, Wilson 1984, Rosenhead 1989b). Rosenhead (1989b), Checkland (1983) and Wilson (1984) argue that classical MP fails to see the world in which decisions are made as being peopled by purposeful human beings and by groups of such individuals aggregated by imperfectly shared interest. Elements and relationships are treated as if they were not problematic as to interpretation and influence and as if they were as predictable and stable as behaviour under natural laws.

The critical elements of MP approaches as they apply to resource management may be summarised as follows:

(a) MP carries an implicit assumption that a single agency could/should deploy a unitary set of goals and or agreed objectives.

(b) MP is unable to model fundamental feedback relationships that determine the dynamics of the system.

(c) MP is too abstract to facilitate inductive learning on the part of decision makers and their advisers.

(d) The process of identifying and representing the problem objective is reductionist. Assumptions of single relationships within, say, a financial consideration only contribute to the setting of an openly clearly biased problem objective: since the objective is merely financial it cannot represent the multiple non-financial relationships and interrelatedness of the system in analysis. A simple unique discrete solution to the system contradicts fundamental management principles encompassed in planning scenarios (e.g. goals are not discrete at all, therefore they are incompatible with MP if the solution of the technique is the ending point of the system action).

(e) MP is falsely characterised as holistic. This assumption is not realistic, it depends on the analyst using the outcomes of the technique in conjunction with other available techniques of systems analysis.

(f) Enterprises and the resource pool are broken down into individual groups, without functional interaction, for prescribed resource allocations based only on financial considerations. People are treated merely as passive inputs in the system, in contrast to the more enlightened thinking of contemporary management science where managers apply enriched decision-making processes with strong human interaction rather than concentrating exclusively on optimal solutions.

(g) The established competition between enterprises for resources and for a place in the optimal solution, though logical under the assumptions of the technique, does not seem to reflect the reality of the farm system. There are interrelationships between resources and environmental conditions at the farm level that cannot be captured solely in a mathematical algorithm.

(h) MP assumes a single decision-maker with objectives conditioned toward financial expectations. From this decision-maker concrete actions can be deduced for implementation through a hierarchical chain of command. The remaining non-financial objectives of the system are unclear, not determined and do not have an allocated space within the overall decision-making chain of the quantitative model.

A logically conflicting element of MP following Rittel and Webber's (1973) is that the formulation of problems is only finally arrived at when a solution has been envisaged. MP becomes operational only after the most important decisions have been made. If decisions are made during or after problem definition, as is the normal expected process, MP conflicts with the intuition and practice of decision-making for managerial purposes.

5.3 The Optimal Stochastic Planning Model of this Study

Following Anderson (1981) and Pandey and Anderson (1988), Figure 5.2 describes the perception of embedded risk in the farm system which, together with the conceptual maps previously elaborated, was used to visualise the stochastic components of a farm model. In a farm model the variables of climate, crop production yield, animal yield, economy, market and finance may be treated as stochastic. Similarly all the variables related to ecosystem resources and directly affecting sustainability are treated as stochastic system components. Critical variables from these components may be identified, and their historical probability distributions, or the farmer's subjective probability estimates, may be worked out in order to use risk management techniques that account for the variability of many of these critical variables in the programming model. Estimates of the probability density functions for the selected critical variables of the farm system are worked out from historical data pertinent to the farm. Where objective probabilities can not be derived, subjective probability weighted values of the events are used, in a similar way to that described by Anderson (1983) for the setting of risky gross margins.

5.3.1 The mathematical structure of the farm model

Supporting Hazell and Norton's (1986) statement that farmers have a preference for continuous survival first and a profit-oriented objective second, the safety-first approach was considered to be the suitable quantitative framework for this study.

The safety-first principle is equivalent to chance-constrained programming, consisting of maximising an objective function subject to a constraint on disaster represented in terms of an exogenously specified crucial probability and a target reference-value (Anderson 1983; Parton 1989), though in the case of this study this condition has been differently broken down for technical and for attitudinal risk. The rule is to maximise expected performance under the constraint that the probability of an outcome less than the specified critical value does not fall under a predetermined level. It involves minimising the probability that some attribute (a_i) falls below a specified critical level d, i.e. minimise $p(a_i < d)$ or minimise F(d) where F denotes the cumulative distribution

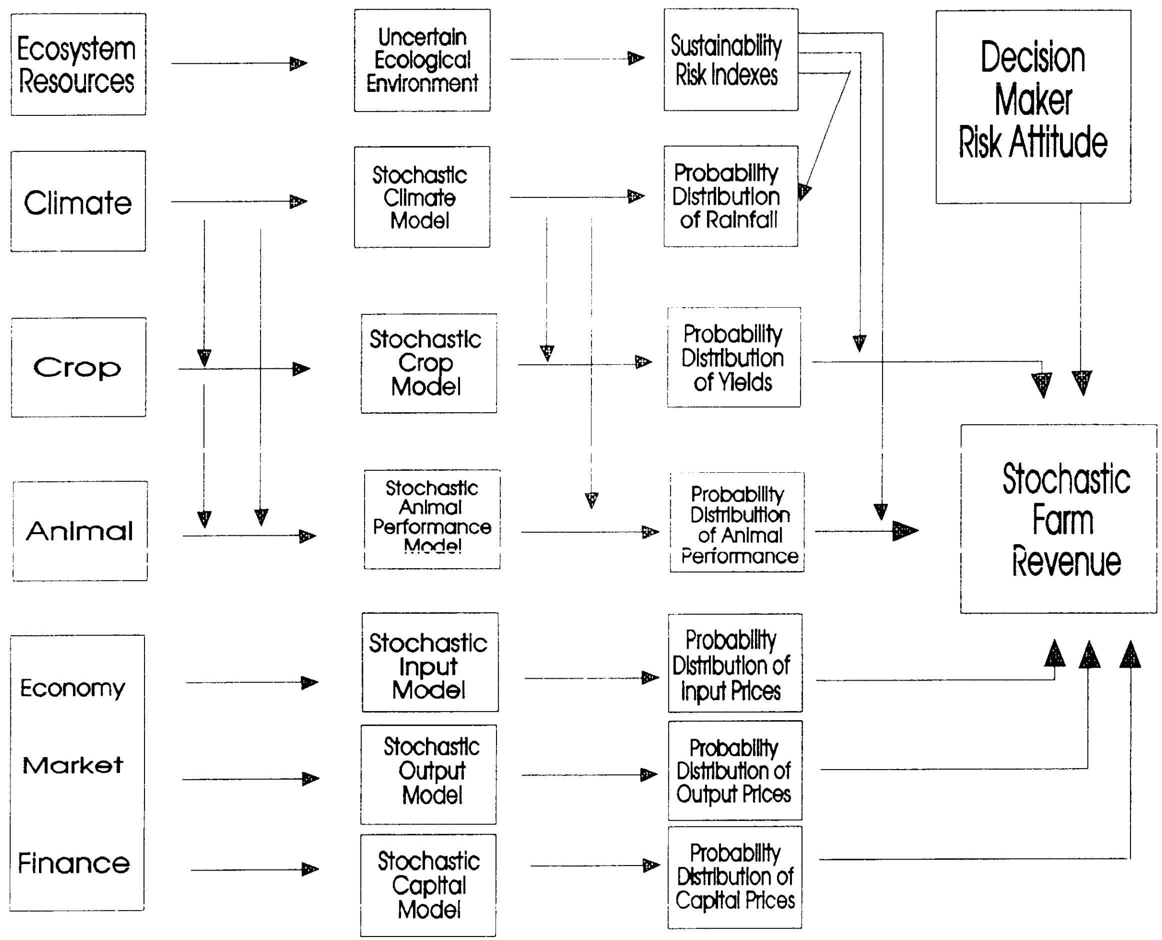


Figure 5.2 The Stochastic Farm Environment

Modified from Anderson (1981), Pandey and Anderson (1988) TH-6-2.GEM function of the i-th prospect (Anderson 1983, p.47). This probabilistic outcome of the variables in analysis is transferred into the constraint set.

As described in Chapter 4, the procedure for the setting of an holistic context for this study required a process of adaptation and integration of components from different decision criteria within the framework of MP. Wicks and Guise (1978) outlined a breakdown of the overall risk analysis scenario in a bimodal manner to into the input-output coefficients and the objective function. Cock (1968) and Rae (1971a,b) supported the use of probability distribution functions of random events as a method to incorporate technical variability. Tauer (1983) argued for minimising downside risk in the technical random events of the farm operation and modifying the constant relative risk attitude of the decision maker, since target values of reference are incorporated to the model for all the variables deemed stochastic. Lambert and McCarl (1985), Hazell and Norton (1986), Patten *et al.*(1988), Pannell (1988) and Hardaker *et al.*(1991) supported the setting of an exponential objective function of linear segmentation to encompass the risk attitude of the farmer within the guidelines of Pope and Just (1991) for a constant relative risk averse decision maker. The effect of stochastic technical events affecting the current farm operation (i.e. farm profit) and attitudinal risk affecting farm wealth (i.e. farm net worth) was discussed by Lambert and McCarl (1985) and Pope and Just (1991).

Integrating the preceding recommendations the MP representation adopted for this study is defined as follows:

$$\text{Max } E(Z) = \Sigma\{(\Sigma a_i X_j + \Sigma \lambda a_i X_j) + W_0^{(1-r)}\} \qquad \text{(Equation 1)}$$

subject to,

$$\Sigma\, a_i\, X_j \leq b_i \qquad \text{(Equation 2)}$$

$$(\Sigma\, c_{is}\, X_j + Y_n) \geq T_1 \qquad \text{(Equation 3)}$$

$$(\Sigma\, a_{is}\, X_j + X_n) \geq T_n \qquad \text{(Equation 4)}$$

$$\Sigma\, p_n Y_n = \lambda \qquad \text{(Equation 5)}$$

$$\Sigma\, p_n Y_n = \lambda \qquad \text{(Equation 6)}$$

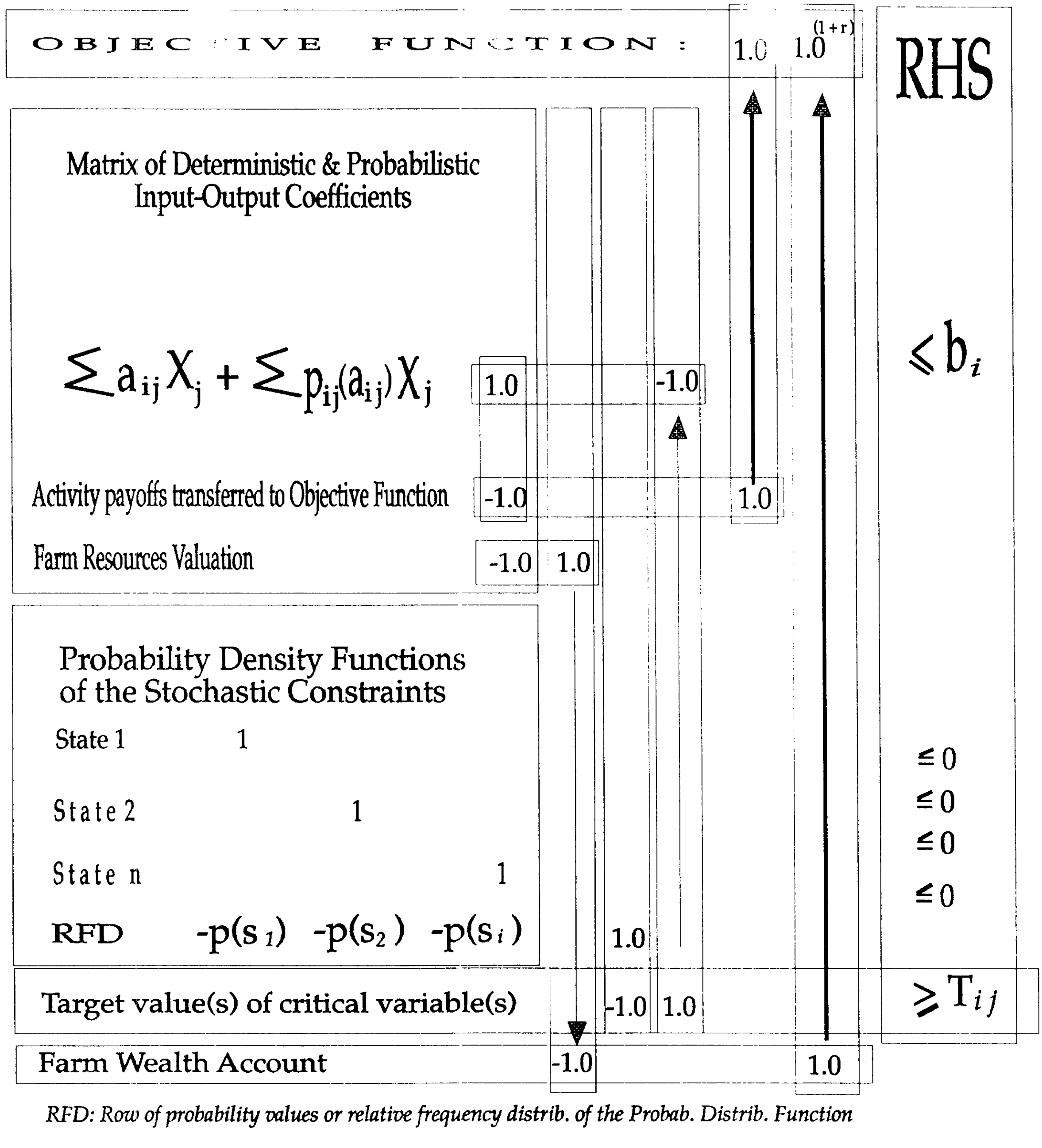
$$X_j \geq 0 \qquad \text{(Equation 7)}$$

where

$E(Z)$	=	expected return of the farm system;
λ	=	probabilistic effect (i.e technical risk) of random enterprises with stochastic input-output coefficients; constant parameterised from 0 to 1;
$(1-r)$	=	exponential effect of the decision-maker's risk attitude with variable coefficient of risk aversion (r);
W_0	=	initial wealth (i.e. net worth);
c_i	=	expected return i-th of the activity j-th;
X_j	=	level of the activity j-th;
a_i	=	technical requirement of the constraint i-th for activity j-th;
b_i	=	level of resource or constraint i-th;
T_1	=	target level of financial input variables;
T_n	=	target level for other technical stochastic input variables;
c_{is}	=	return of the activity j-th for state of nature s;
$(\Sigma\ c_{is}\ X_j - Y_n)$	$\geq T$ =	Target constraint for financial variables;
$(\Sigma\ a_{is}\ X_j - X_n)$	$\geq T$ =	Target constraint for other technical variables;
Y_n	=	deviation below target for financial state of nature n;
X_n	=	deviation below target for other non-financial state of nature n;
p_n	=	probability that observation n will occur;
n	=	number of activities; and
s	=	number of states of nature.
r	=	variable coefficient of risk aversion;

5.3.2 The operational structure of the farm model

Figure 5.3 visualises the mathematical structure of the MP matrix in a graphical manner. An operational description of its components follows. This description aims to provide a complete understanding of the programming components of the holistic stochastic management process developed in this study.



RFD: Row of probability values or relative frequency distrib. of the Probab. Distrib. Function

Figure 5.3 Diagram of the Stochastic Programming Model

(a) The programming matrix

The general arrangement of the programming matrix incorporates: (i) activities or **decision variables**; (ii) resources and constraints called **model equations** and; (iii) an **objective function**.

(i) Decision variables

Pasture and crop activities. The pasture activity supplies the farm system with an average of 9.5 DSE/ha. Forage crops are produced for fodder. Hay and silage are primarily allocated to the steers whilst oats are used for ewes in the breeding season. There is a total area of 150 ha permanently allocated to these cropping activities. For this reason, crop rotations are not considered within the model.

Fixed assets activity. This activity imports the value of the capital investments into the farm wealth account.

Livestock valuation activities. This activity imports the value of the livestock inventory into the farm wealth account.

Animal production activities. The animal production activities for the beef enterprise are: cows, first-calf heifers, calves, weaners, vealers, replacement heifers, steers and bulls. The animal production activities for the meat enterprise are: Merino ewes, crossbred ewes, Coopworth rams, first-cross sucker lambs, first-cross female hoggets, first-cross male prime lambs, second-cross sucker lambs and second-cross prime lambs. The animal production activities for the wool enterprise are: Merino ewes, Merino rams, suckers, female weaners, wether weaners, female hoggets, and wethers.

The breeding, replacement and fattening animals are purchased off-farm. Their supply is assumed to be perfectly elastic and constrained only by the physical capacity of the farm and the availability of cash to buy animals.

The breeding animal activities (i.e. cows, first-calf heifers, ewes) supply calves and lambs respectively. Animal activities transfer to the sale pool a given percentage of culled animals.

Animal feeding activities. The feeding activities ensure the food resources for the animal enterprises. A DSE feeding value for each animal category links these activities with the available food. These activities carry the variable cost per animal unit.

Animal transferring activities. These activities use an index to transfer the animals between age groups.

Buying activities. These activities supply the farm model with the necessary number of animals. The purchase cost is subtracted from the bank account.

Land purchase. Purchase of land is an introduced activity to allow the generation of capital gains through land acquisition.

Selling activities. Animals are sold from the sale pools and the income is transferred to the bank account.

Transfer activities of probabilistic values of critical variables. These activities transfer the values of each observation of the critical variables weighted by a relative frequency distribution (RFD) index to the target constraint.

Transfer activities of minimised deviation values of critical variables. These activities transfer the minimised negative deviation value of the critical variables to the input-output coefficients set.

Financial and banking activities. This set of activities encompasses cash usage, overdraft usage and payment, loan usage and payment, payment of variable and fixed costs, and transferring of the bank account balance to a saving account.

Operational profit transfer. Using this activity the model transfers the balance of the bank saving account to the objective function.

Farm wealth transfer. Using this activity the model transfers the farm wealth balance to the objective function.

(ii) **Model equations**

Resources

Land inventory. The farm's land area is separated into two categories. The former is livestock land (LLAND) allocated to improved pastures. The latter is cropping land (CLAND) used for on-farm fodder consumption.

Building and improvements valuation. Capital invested in buildings and improvements is incorporated in the model for farm wealth accounting using written down values.

Machinery and vehicles valuation. The values from the farm survey are included for farm wealth accounting purposes.

Animal inventories. This is a set of equations for each one of the animal enterprises. The model has been set in such a way that all the current farm animals are either available for sale at the beginning of the planning period within the sale pool or used for farming purposes. If the animals are sold beforehand the money is made available from a cash account (CASH).

Crops on-hand. The allocated cropping land (CLAND) is used to produce hay, silage and oats for supplementary feeding of specific animal groups in critical seasonal and biological periods.

Technical parameters and constraints

Forage crops allocation per animal group. These constraints distribute the available forage crops between animal activities. Hay and silage are used for steers, and oats and silage are used for breeding ewes and prime lambs.

Crop yields per hectare. This is a constraint that defines the level of yield for forage crops coming from a hectare of crop land.

Stocking rate in DSE. This constraint establishes the relationship between the pasture (amount of food in DSE/ha) and the animal activities. Each animal activity has a DSE-food requirement which is the value that is taken from the available crop.

Breeding-feeding ties. These are technical constraints that link the production activities with the animal feeding activities.

Cows:bull ratios. This constraint establishes the number of cows to be serviced by one bull.

Biological parameters of animal performance. The major biological parameters are calving rate and lambing rate. These values are taken when marking calves and weaning lambs.

Marketing constraints

Sale casting ratios and animal-sale pools. The equations of the sale pool receive the animals coming from the animal activities through the casting indexes.

Wool pool. The meat sheep and wool enterprises produce wool that is sold through a pool.

Market limit to purchases. Marketing equations contain marketing constraints for sale and purchase of animals.

Land availability for purchase. This equation provides a land purchase option to the system constraining available land area. A land sale option may be arranged.

Financial constraints

Variable costs. This equation contains the variable costs per activity-unit of the farm system.

Fixed costs. This equation contains the fixed costs as a RHS value. A "pay fixed costs" activity subtracts the total value of the fixed costs from the bank account.

Overdraft constraint. This equation provides a limit to the available amount of money to be used by the overdraft option. There is a complementary equation called an "overdraft tie" that links the overdraft activity with the payment of the overdraft within the period of analysis.

Loan constraint. This equation provides a constraint for the available loan option. There is a complementary equation called "loan tie" that links the loan-raising activity with the payment of the loan plus interest within the period of analysis. Longer repayment periods may be considered within this constraint by establishing a set of payment indexes and transferring the negative balance of the loan to the farm wealth account.

Cash account. This equation offers an initial amount of cash available to the farm system, mainly from the sale of assets at the beginning of the planning period and surplus from the previous period.

Bank account. This constitutes the key equation in the financial operation of the system that provides activities with a source of funds for the purchase of animals and other assets and subtracting of costs. The balance of the bank account is transferred, using a transfer activity, to a bank saving account.

Saving account. This equation receives the balance of the bank account and applies an interest rate. From this equation, the model uses a maximisation transfer index of the balance of this account as operating profit to the objective function.

Farm wealth. At the end of the period this equation receives the net values of all farm assets. An index is set up to transfer the balance of this equation to the objective function.

Constraints of risky variables. The set of probabilistic values for the critical variables of the farm system are formulated as one row per observation. Each row contains the value plus a transfer index to a weighted index row (or probabilistic value of the set of observations). From there the weighted observations are taken to minimise the negative deviation from a target value. A transfer activity takes the parameter of the critical constraint to the input-output set to be used for the optimising exercise. The complete list of risky constraints is defined further in this chapter [i.e. (c) The risk components of the programming matrix].

(iii) The objective function

The objective function maximises expected farm equity constituted by current profit of the farm exercise and farm wealth. The farm profit account (i.e. bank saving account) receives the financial values of the current exercise. The farm wealth account receives the assets and inventory values. The balance of these accounts are sent to the objective function using transferring indexes. Farm wealth is modified in the stochastic scenarios by an exponential factor that encompasses the effect of attitudinal risk in farm equity.

The codes and components of the model equations, decision variables and objective function can be seen in the output files of Appendix 6.1.

(b) **The data collection area**

The model imports the information through the data collection area and transfers these data on to a programming matrix. The data collection area and the programming matrix are spreadsheet files (*.WK3). A macro developed by Antony (pers comm 1990) is used to convert the spreadsheet into a MPS input format (*.GMS) readable by MP software. This study uses General Algebraic Modelling System (GAMS) developed by Brooke, Kendrick and Meeraus (1992). The GAMS output file (*.LST) is converted to a word processing file (*.DOC) using Word Perfect 5.1 for editing and printing purposes. The components of the operational structure of the programming model are detailed in Figure 5.4.

(c) **The risk component of the programming matrix**

The integration between the constraints and the activities in the stochastic input-output coefficients of the programming matrix is described using only one critical variable as an example and is illustrated in Figure 5.5.

Figure 5.5 shows the constraint labelled "lambing rate" where the a_{ij} deterministic coefficient has been crossed out. This is the critical parameter to be generated by the stochastic vector set through a modified safety-first approach. The values gathered on lambing rate are weighted with a probabilistic index using a relative frequency distribution of farm data or a farmer's subjective probability approach of weighted values related to future farm performance. A transfer activity integrates the row of weighted observations with the target row to minimise the negative deviations relative to that target value. The target value has been generated using the expected value of the probability density function of farm data. Similarly, weighted indexes are used to incorporate stochastic effects of soft system variables such as sustainability. An extended description of this exercise is found in Appendix 5.3.

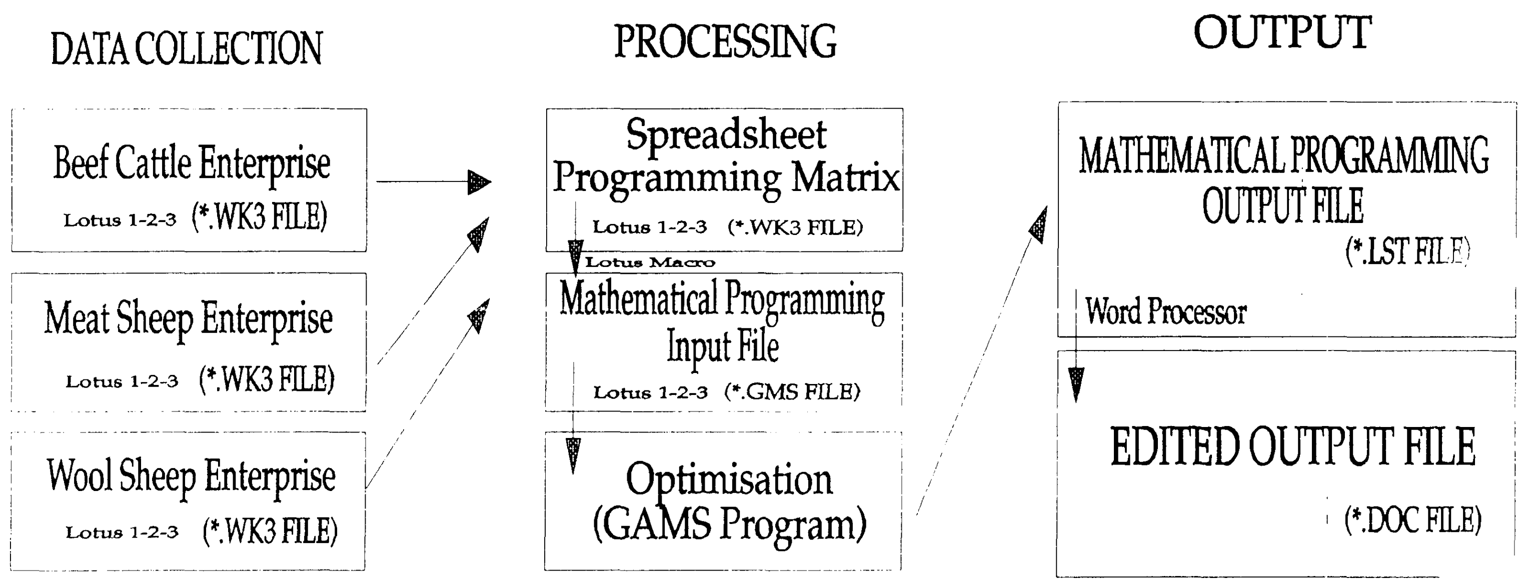


Figure 5.4 The Operational Structure of the Analytical Process

TH-55-1.GEM

	LHS		BREEDING EWE	TRANSFER LAMBING RATE OBS.1	TRANSFER LAMBING RATE OBS.2	TRANSFER LAMBING RATE OBS.3	TRANSFER LAMBING RATE OBS.4	TRANSFER LAMBING RATE OBS.5	TRANSFER WEIGHTED L.R.TO TARGET ROW	TRANSFER TO PARAMETER PLACE
LAMBING RATE	0.00	≥	~~- 0.85~~							- 1.00
OBSERVATION 1	0.00	≥	- 0.85	1.00						
OBSERVATION 2	0.00	≥	- 0.90		1.00					
OBSERVATION 3	0.00	≥	- 1.00			1.00				
OBSERVATION 4	0.00	≥	- 1.05				1.00			
OBSERVATION 5	0.00	≥	- 1.10					1.00		
WEIGHTED PROBAB.	0.00	≥		- 0.05	- 0.14	- 0.33	- 0.29	- 0.19	1.00	
TARGET LAMBING RATE	- 0.90	≤							- 1.00	1.00

Figure 5.5 Management of Technical Risk in the Input-output Set of the Programming Matrix

The critical variables considered probabilistic within the input-output set of parameters are described in Appendix 5.2. A density function for each of these variables is arranged, complemented with a basic statistical confidence analysis. The data used came from five years of observations on the case-study farm. The target values of the critical variables were generated using the expected value of the probability distribution of data. The estimation was conducted using the "t" statistics, considering the farm as a finite population and following guidelines of Keller et al. (1990, p. 283). A statistical non-significance level for the parameter expresses a high variation in the set of data in analysis, making stochastic analysis even more necessary for this critical variable.

The list of the selected random variables of the farm system is as follows:

(i) Calving rate for breeding cows.
(ii) Calving rate for first-calf heifers.
(iii)) Stocking rate per unit of land (ha).
(iv) Sale price per fat steer.
(v) Sale price per culled cow.
(vi) Lambing rate for 1X-breeding ewes
(vii) Lambing rate for 2X-breeding ewes.
(viii) Sale price per 1X-prime lamb.
(ix) Sale price per 2X-prime lamb.
(x) Lambing rate for merino ewes.
(xi) Sale price for AAA wool.
(xii) Sale price for AAAH wool
(xiii) Land price.
(xiv) Sustainability effect in farm performance.

Probability distributions were generated for the whole set of stochastic variables using historical data, excepting for the "sustainability" variable where a subjective approach was undertaken. This was done since the farmer did not have available historidal data on stocking rate (SR) as it is recommended in Appendix 5.3, p. 218, par.1.

(d) The scenarios of the programming model

The programming model encompasses two scenarios. The first scenario is a deterministic exercise maximising farm equity. The second scenario is a stochastic exercise maximising farm equity as per the guidelines of this study. Farm assets and farm equity analysis are currently more relevant exercises than gross and net return exercises. The former are indicators of whole-farm productivity and farm capital contribution; the latter are partial indicators of farm performance affecting either farm liquidity or farm wealth.

Each of the scenarios has a set of files as previously described in this chapter: (a) a Lotus file (*.WK3); (b) a MP input file (*.GMS); (c) a MP output file (*.LST), and; (d) an ASCII file (*.DOC).

The programming matrices or input files of these models are in Appendix 6.1.

5.4 A Demonstrative Deterministic and Stochastic Farm Model

A simulated small-farm environment was arranged as it is presented in Appendix 5.4. The model was run with two scenarios.

The first scenario (or farm plan 1) encompasses a simple deterministic MP problem. The latter scenario (or farm plan 2) is stochastically modified for the variables considered critical within the system: lambing rate (LR) and land-carrying capacity (CCAP). Farm performace, in terms of DSE/ha, is affected by a density function, which serves to represent the effect of maintaining sustainability. The farmer theoretically allows for a 10 per cent downside effect on stocking rate because of ecosystem degradation effects, since his/her target probabilistic value is set at 0.90.

The deterministic option (farm plan 1) was run using a value of 100 per cent for lambing rate and 8.5 DSE/ha or 0.2117 ha/ewe. For the stochastic exercise (farm plan 2) these discrete values were replaced by sets of historical data arranged in density functions containing values of the random variables with their associated probability values. Target values were established, below which the model should minimise the downside risk of the random variables. The farmer exhibits a constant relative risk aversion with tendency to risk taking (r = 0.000001). The programming matrices and the input-output coefficients used may be analysed in Appendix 5.4.

The farm equity of farm plan 1 was $6032 while that of the farm plan 2 was $5276. Afterwards the model was parameterised for the critical variable 2, one level (50 per cent) below the initial level and one level (50 per cent) above the initial level. This enabled a linear segment of farm equity to be built that represents the function domains of the two farm plans depending upon the fluctuations of the critical variables. The linear segment of the function domains for the deterministic and stochastic farm plans may be observed in Figure 5.7. Tables 5.1 and 5.2 summarise the parameterisation exercise for both scenarios.

Table 5.1 Parameterisation of the Deterministic Test Model

Stages	LR	DSE	Optimal Solutions	RFD
50% below standard	0.50	4.25	$5,254.00	0.28
Standard Optimal Farm Plan	1.00	8.50	$6,032.00	0.32
50% above standard	1.50	12.75	$7,657.00	0.40

LR: Lambing rate;

DSE: Dry sheep equivalent;

RFD: Relative frequency distribution

Table 5.2 Parameterisation of the Stochastic Test Model

Stages	LR	DSE	Optimal Solution	RFD
50% below standard	0.50	3.82	$ 5,267.00	.332
Standard Optimal Farm Plan	1.00	7.65	$ 5,276.00	.333
50% above standard	1.50	11.47	$ 5,289.00	.334

The linear segment of farm plan 1 was generated within a range of $5254 to $7657. The farm plan 2 segment was generated within a range of $5267 to $5289. Farm plan 2 showed a less dispersed distribution of farm revenue than farm plan 1. The value of the expected farm equity in farm plan 2 was smaller than that of farm plan 1, consistent with traditional expectations of stochastic analysis. There are some similarities in results with those described by Parton (1992, p.116) though for this study the technical constraints were parameterised for values below and above the targets.

Making an assumption of normality in the distribution of farm incomes it is possible to do some basic statistical analysis. Farm plan 1 has a standard deviation of $1001 and a coefficient of variation of 15.85 per cent indicating a high relative variability in expected farm income. Farm plan 2 has a standard deviation of $4.5 and a coefficient of variation of 0.1 per cent. Therefore farm plan 2 is showing a farm income distribution which better suits planning purposes. Using this information as a simple criterion for risk analysis purposes, it may be said that farm plan 1 is riskier than farm plan 2 because of the higher value of the coefficient of variation. Consequently the usage of the stochastic algorithm in the programming matrix of farm plan 2 has a positive effect in the management of income-variance, since it minimises the negative deviations below the target of the risky variables of the farm system. This has an impact in decision making under risk since the farmer has, rather than deterministic information, a set of more valuable stochastic information. This situation may be observed in Figure 5.6

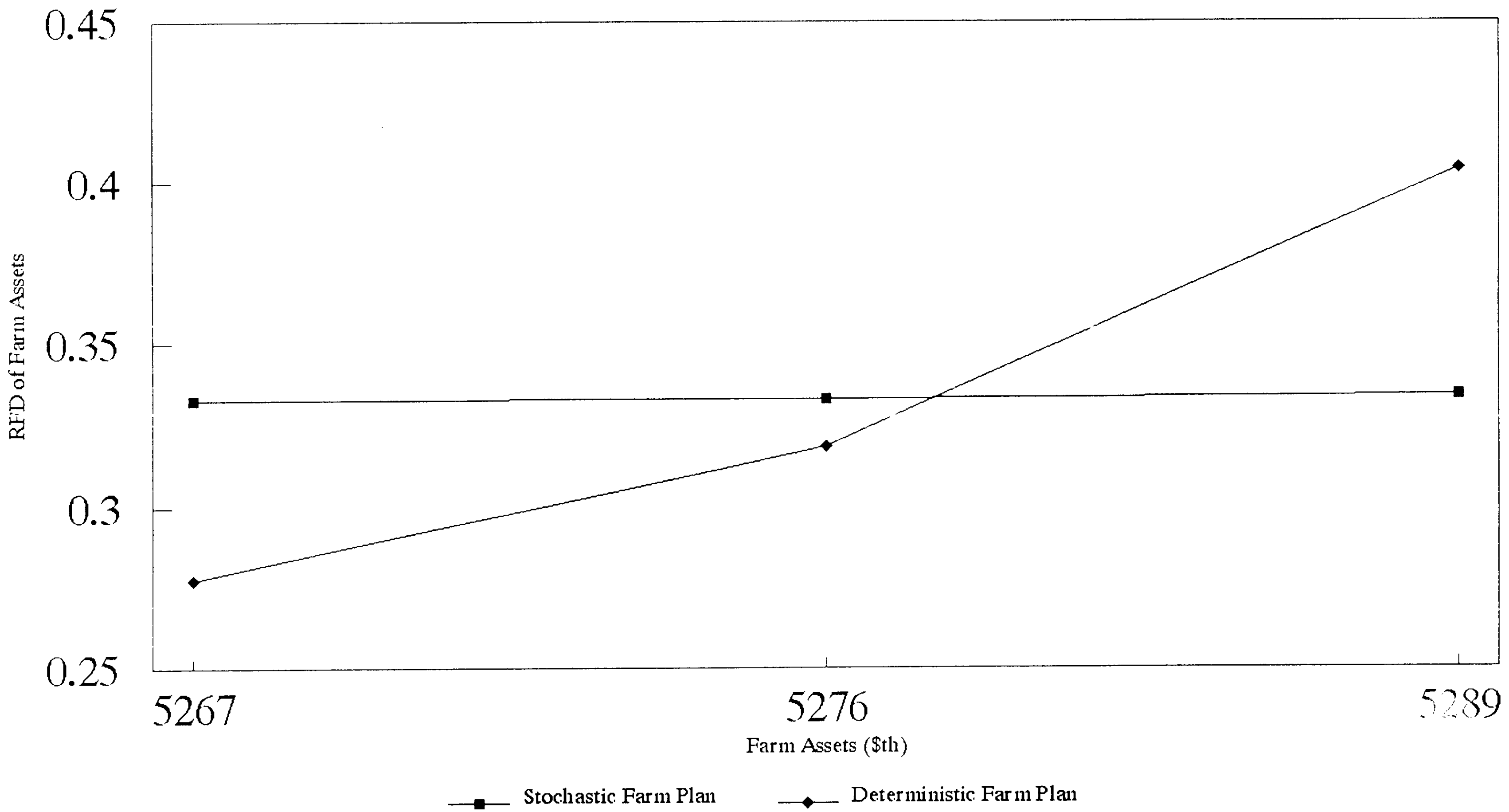


Figure 5.6 Deterministic and Stochastic Demonstrative Farm Plans

5.5 Summary

Chapter 5 has presented the MP modelling technique of this study. A brief overview of stochastic modelling assumptions was presented using the description in the safety-first approach as a reference point.

MP models are explained and conceptual and analytical models are defined for the farm case-study. Extensions of LP provide algorithms to handle risk in the programming model. A multi-integrative stochastic model has been defined for the purposes of this study, where technical risk is accounted for in the input-output coefficients of the programming matrix, affecting farm profit; and attitudinal risk is accounted for in the objective function of the programming matrix, affecting farm wealth. Both are finally integrated to produce a stochastic optimal farm equity value. The model addresses some of the soft systems elements that are the domain of holistic analysis outlined in chapter 2 to 4.

A mathematical formulation of the MP farm model is developed and the operational structure of the farm model is described. Finally a two-fold scenario for a demonstrative case-study is used to compare the application of the stochastic model (i.e. deterministic vs stochastic scenarios).

After comparing the results of the two scenarios of the test model it may be concluded that the management of technical and attitudinal risks has a defined influence in total farm performance. An overall comparison between the two scenarios in analysis implies a different perception of management strategies when deterministic and stochastic information are available to the decision maker.

The final stage of this research is to place the stochastic model, with its two risk components (technical and attitudinal) back into the holistic framework of the case-study. This re-integrative stage, together with the setting of conclusions of the study and its implications are the tasks of Chapters 6 and 7.