Some Practical Aspects of Stochastic Budgeting

by

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Abstract

In this paper, the rationale for modelling in a probabilistic framework is presented. The discussion then focuses on stochastic budgeting as a specific application of the stochastic simulation technique. The process of the development of the RISKFARM model at the University of New England is presented as a backdrop for identifying and discussing the practical difficulties associated with stochastic budgeting. These include determining and accounting for stochastic dependencies and the data-hungry nature of these types of models. Reference is made to a recent application of the RISKFARM model.

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Introduction

Traditional farm planning and budgeting approaches use single, 'point' estimates of production, market and financial variables to predict point results. Estimates of these variables must be used because the values which will actually occur are not known with certainty. Typically, the point estimates used are the expected values (means) or 'most likely' values (modes) of the variables.[1]

Regardless of the estimate selected, in reality many of the events and conditions planned for will not turn out as assumed. The planner may have been too optimistic with respect to some estimates and too conservative with others. The combined errors in each estimate may, and often will, lead to an estimated result that is significantly different to the one actually experienced. This problem is exacerbated if, as is most likely, the system being modelled is non-linear. As illustrated in Figure 1, if $y = f(x)$, where x is stochastic, then $y^* = f(E[x]) > E[y]$ if $f'(x) < 0$. That is, the effect of departures from the (mean) point estimates in non-linear systems are more severe than in linear systems. This is a management problem associated with operating in an uncertain environment.

One common response to this problem is to conduct sensitivity tests as part of the planning exercise in order to determine the range of possible results. Sensitivity analysis involves simulating the results of various 'What if?' scenarios which combine different, plausible, sets of values for the uncertain variables. (See, for example, Pearce 1983.) This type of analysis provides an indication not only of the outcomes that might be achieved but also the response in the magnitude of the outcome to changes in each variable. The variables that generate the most change in the magnitude of the outcome as they themselves change are often regarded as those that are most crucial to the achievement of the planner's objectives. However, 'sensitivity analysis, while a valid and useful technique for determining the range of possible outcomes, does not give any indication of the likelihood of a particular result being achieved' (Milham and Hardaker 1990, p.6).

There is general agreement that the likelihood's of outcomes do concern decision makers and that it makes little difference for a decision whether these

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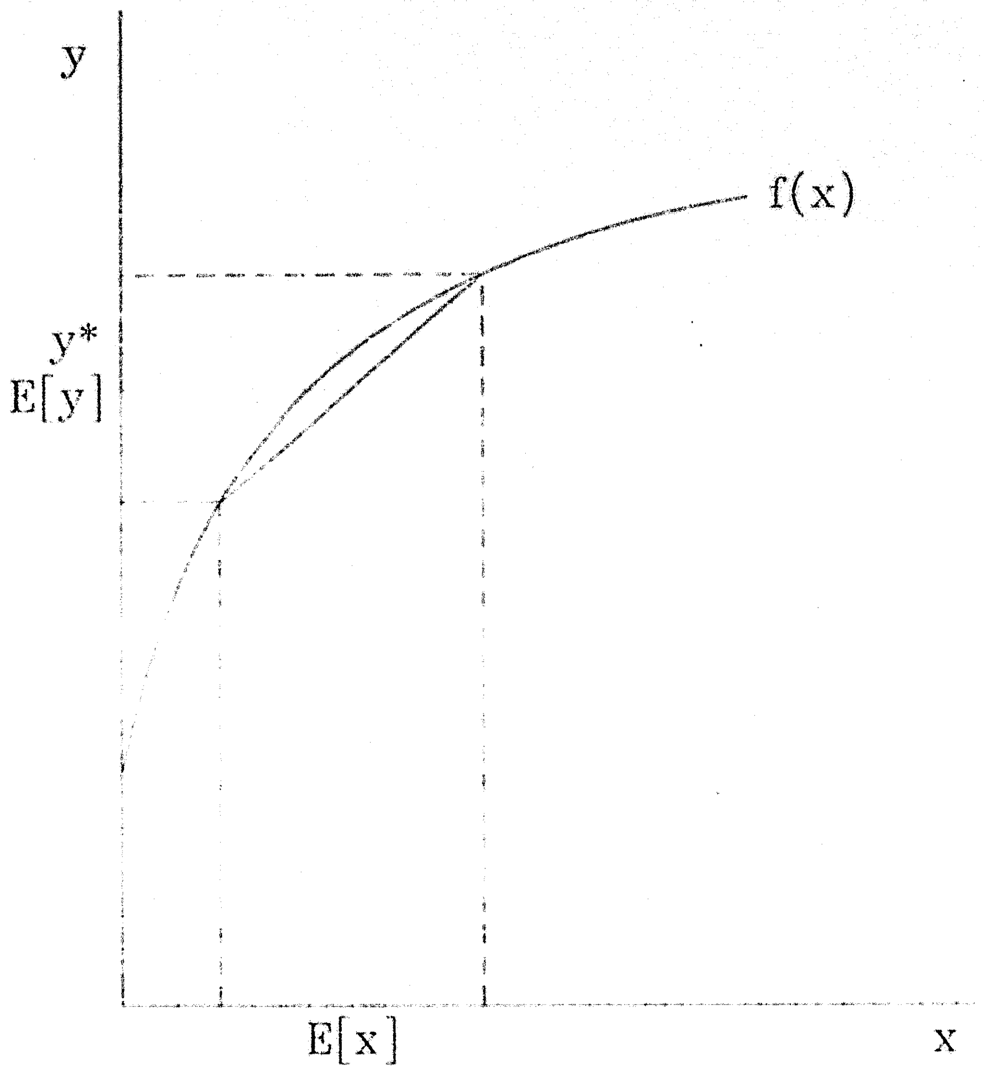
[1]It is generally recommended that mean values be used (Anderson with Hardaker 1985; Little and Mirrlees 1974; Reutlinger 1970), although under many distributional assumptions, mean and mode will be identical, or nearly so.

Figure 1

The Expected Values of Linear and Non-Linear Systems Under Risk



likelihood's are judgements based on mere hunches or on 'expert' advice or on an enormous amount of frequency evidence (Anderson *et al.* 1977; Andrews 1987; Eidman 1987; Malcolm *et al.* 1982; Reutlinger 1970). Furthermore, it has long been recognised that, 'since the likelihood of outcomes and, to a more limited extent, even the full range of outcomes cannot be objectively determined, ...the evaluation of risk is essentially subjective' (Reutlinger, p.9). If subjective probabilities are implied in real behaviour, then models and analyses that do not make these explicit in a systematic manner will be seriously deficient.

The Probabilistic Approach

The probabilistic approach to modelling and analysis makes use of more information and also provides more information to the decision maker. The projections of the consequences of a particular strategy or event should as nearly as possible reflect what the expert analyst believes to be the possible outcomes of that event under explicitly stated conditions. If required to appraise and summarise the consequences of the event in terms of a unique number, the expert must ignore a great deal of his or her knowledge about the event. Also, the temptation is there to give an estimate which reflects the decision maker's perceived preference or aversion towards risk. The alternatives include giving a conservative estimate, i.e., one that is known to have a high probability of being exceeded, giving what is believed to be the most likely outcome, or giving the mean of several outcomes etc. Consequently, the decision maker, who must consider the riskiness of various alternatives in choosing between them, is deprived of knowledge of the likelihood of realising different outcomes and is in an equally difficult position (Cassidy *et al.* 1970; Hertz 1964).[2] It is difficult to dispute the claim made by Reutlinger so many years ago that 'in a world of uncertainty the only correct and useful knowledge and information is that which is reported in probability terms and can be refuted in these terms' (Reutlinger 1970, p.12).

An implicit assumption in the above discussion has been that imprecision or uncertainty in understanding is best and most operationally encoded through probability distributions. Whenever a system is modelled imperfectly, which will likely apply to all models at some level of detail, the model should properly become probabilistic to capture the precision of understanding. Arguing in this style, Mihram educed an uncertainty principle of modelling: 'Refinement in modelling eventuates a requirement for stochasticity' (Mihram 1972, p.15), from which he draws the corollary that the more conscientiously developed the model the more likely it will be stochastic in nature.

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[2] Anderson (1976, p.221) points out that the only careful decision makers who can afford to be guided by single-value estimates are those who are completely indifferent to risk.

Simulation models, which are the most flexible and least confined of symbolic models, can accommodate stochasticity easily and directly. They thus often find favour over models that are more restrictive and less-easily modified to accommodate stochastic variables and relationships when refined modelling is undertaken (Anderson 1974; Anderson *et al.*; Barry 1984; Cassidy *et al.*). In agricultural economics in particular, recourse is often made to simulation as the only approach feasible in coming to grips adequately with the inherently dynamic and stochastic nature of the problems posed (e.g., Anderson 1974; Brommell 1991; Walker and Helmers 1984). Indeed, stochastic simulation models are claimed to be the most widely used models for risk analysis or project appraisal under uncertainty (Anderson with Hardaker 1985, p.12).

The practical implementation of stochastic simulation modelling commonly involves the approach of Monte Carlo sampling. Anderson (1983) notes that when random variables enter a production function, even when they are normally distributed, the resulting random variable will not be a member of the same family of distributions.[3] 'Analytical methods thus fail [and] the only feasible approach for resolution of the problem appears to be the crude "block-busting" method of Monte Carlo sampling' (Anderson 1983, p.9). In this approach variates are randomly sampled from probability distributions specified in the model to compute empirical distributions, or risk profiles, for critical outcomes. In brief: for a particular simulation, values of parameters entering into the model are chosen by Monte Carlo selection and combined according to the functional relationships in the model to determine an outcome; hence, iterative simulations allow the construction of a cumulative distribution function for the outcome. The key virtue of Monte Carlo sampling is its flexibility and ease of incorporating virtually any stochastic consideration or other relationship that may be desired (Anderson with Hardaker; Cassidy *et al.*).[4]

An important issue in stochastic simulation centres on the specification of the stochastic dependencies within the model. Many writers have reported on the significant biases that can be introduced in projections if contemporaneous or serial correlation relationships are overlooked (e.g., Harrison and Cassidy 1977; Hull 1980; Reutlinger). 'Correlations are difficult to detect, and even more difficult to measure, but overlooking them may lead to a completely wrong interpretation in the analysis' (Pouliquen 1970, p.45). The modeller must therefore be prepared to expend considerable time and effort in determining and incorporating stochastic dependencies even if only in a rudimentary fashion.

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[3]Press (1972) details the only exception, being linear combinations of members of the same, *stable* distribution family.

[4]An excellent exposition of the Monte Carlo sampling approach is contained in Reutlinger (1970)

One approach to this problem is to attempt to measure covariations directly. That is, to empirically estimate the relationship between each pair of variables that are potentially interdependent. To operationalise this in a model would require forecasts for each of the predetermined independent variables. A more streamlined technique is the hierarchy of variables approach (Anderson *et al.*), which is described later in this paper. This approach requires forecast values of only one variable for the analysis to proceed.

Stochastic Budgeting

It is well recognised that the management tasks of planning and monitoring business performance can be critical to both the short-term profitability and the long-term viability of agricultural enterprises. It is also widely accepted that financial accounting and budgeting in a management context can contribute substantially to the performance of these tasks (e.g., see Milham and Hardaker). This being the case, and in light of the above discussion on risk and decision making, an appropriate activity preceding any major investment or major change to farm financial structure would be to undertake dynamic, stochastic budgeting.[5]

Stochastic budgeting in the farming context involves developing a model that mimics the operation of the farm business and provides projections of financial performance while taking account of the uncertainty inherent in many aspects of the decision environment. It is thus simply a special case of the more general approach of stochastic simulation. Analysis of this kind will provide vital information to the decision maker regarding the potential range of financial performance, and the associated likelihood of achieving a particular level of performance, in a particular time period and over the time horizon modelled.

Applied stochastic budgeting thus requires an analytical tool that encompasses whole-farm financial analysis and that enables an assessment of how the level of returns and risk are influenced by alternative financial plans and strategies. An appropriate device for this purpose is a computerised simulation model with the capacity to utilise probabilistic information. RISKFARM (Milham, Hardaker and Powell 1992) is a model of this nature.

The RISKFARM Model

RISKFARM is a computer model for simulating the financial structure and performance of a farm business under uncertainty using management accounting procedures. It is centred

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[5]If the time-frame for making the decision is short and/or the necessary resources, information and skills for undertaking stochastic budgeting are not readily available, then the second-best approach of sensitivity analysis tempered with expert judgement may need to be followed.

around a LOTUS 1-2-3 spreadsheet which serves as the initial interface for data entry by the user. The stochastic processes are handled by the add-in software program @RISK. This program enables the specification of model parameters in probabilistic form, together with any stochastic dependencies between the parameters.

RISKFARM was developed to enable the appraisal of the financial performance and risk effects of alternative farm and non-farm investments and potential changes in the financial structure of a farm business.[6] It was designed to model and simulate agricultural production situations where the decision maker views the uncertain environment in probabilistic terms. Variables that can be analysed include product yields and prices, expenses, asset values, tax obligations, interest rates and other financial conditions. Uncertain values for all of these variables can be specified in a probabilistic form.

RISKFARM is a management-oriented, spreadsheet-based, whole-farm budgeting model which produces annual financial reports over a five year time horizon. That is, the model operates at a strategic rather than month to month tactical level. The financial reports are derived from functional equations linking the farm activities, capital transactions, consumption activities and financing and tax obligations. Flow chart representations of the physical and financial relationships in the model are shown in Figures 2 and 3.

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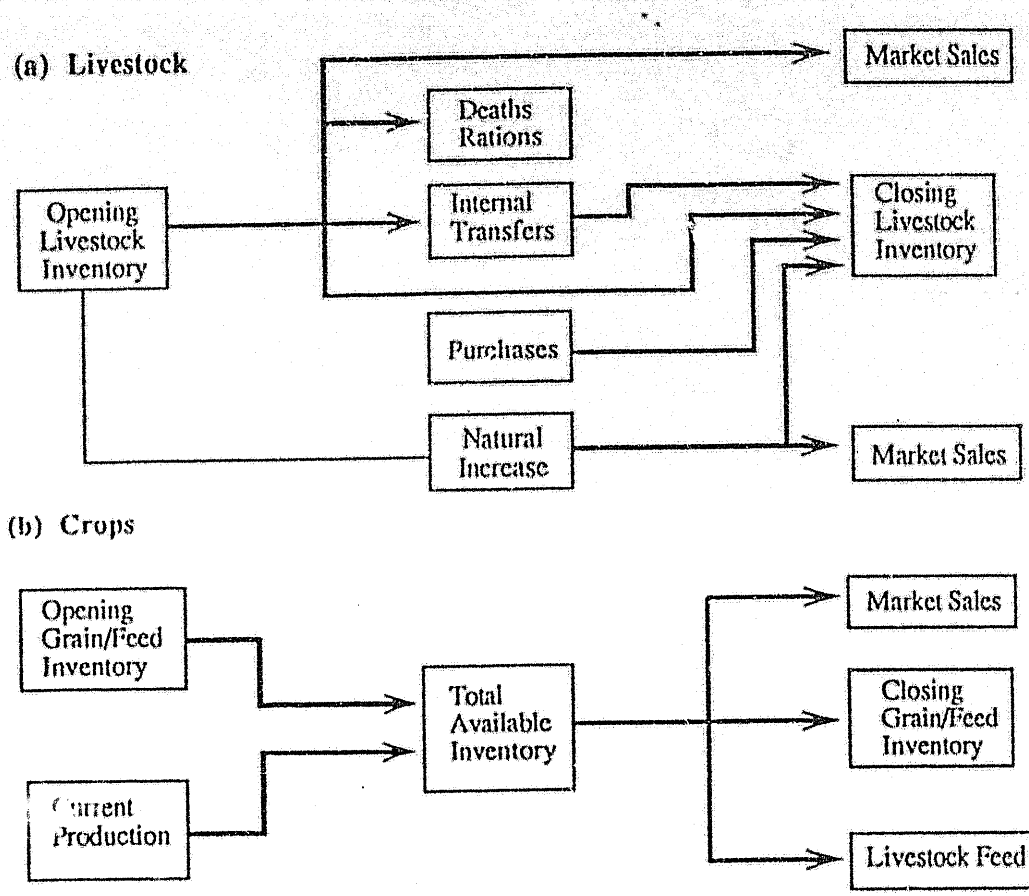
[6]The structure of RISKFARM owes much to the deterministic FFSM model developed at the University of Illinois (Schnitkey *et al.* 1986; 1987). Bosch and Mickey (1987) indicate that a stochastic version of the FFSM may now be available.

Figure 2

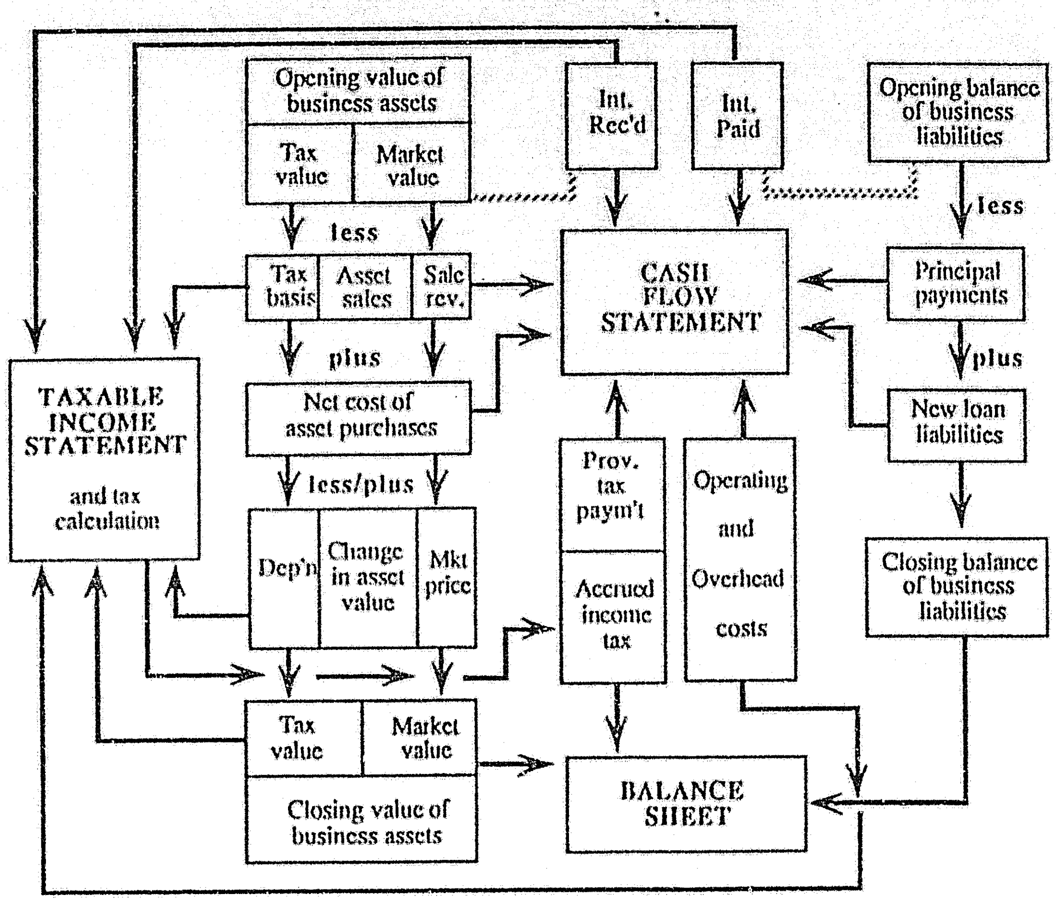
Physical Flows in **RISKFARM**



Source: Milham *et al.* (1992, p4)

Figure 3

Financial Flows in **RISKFARM**



Source: Milham *et al.* (1992, p6)

While RISKFARM operates over a five-year time horizon, only four of the model years are "future" years with uncertain, probabilistic variables. The data for the first model year are extracted from farm records for the last historic financial year. Parameter values for this year are hence known and will not change. This provides a constant starting point for analysing the financial performance and risk effects of alternative farm management strategies.

Risk in RISKFARM

The stochastic variables in RISKFARM include commodity prices, crop and wool yields, livestock weaning and death rates, farm costs, and investment and loan interest rates. Thus, uncertainty in farm production and commodity and financial markets can be accounted for in some detail. The values of all stochastic variables obtained during the sampling process are constrained to be non-negative.

The estimation of the parameters of the probability distributions for the stochastic price variables, and their correlations, is partially empirically based and partially based on elicited subjective expectations. In brief, preliminary estimates of the mean and standard deviation of each price distribution are obtained using regression techniques and the hierarchy of variables approach (Anderson *et al*). This approach indirectly captures any correlation relationships between these parameters. Subjectivity is then allowed for by adjusting the estimated means and variances to account for individual farm business characteristics and grazier expectations.

Application of the hierarchy of variables approach requires the selection of a macro-level variable with which all commodity prices could be expected to be reasonably strongly related. In RISKFARM, for want of a better variable for which four-year forecasts were readily available, the index of commodity prices received maintained by the Australian Bureau of Agricultural and Resource Economics (ABARE 1990), was used as the macro-level variable. Individual commodity prices were regressed against this index to obtain forecasting equations. Forecast values of the price index provided by ABARE were then entered in the estimated equations to predict prices for the commodities. These predictions are assumed to be the means of normal distributions, with the standard errors of the estimates being the standard deviations of those distributions. That is, uncertain commodity prices are assumed to be normally distributed, with means and standard deviations derived by regression techniques. This approach requires the assumption that the historic relationships amongst the commodity prices, and between the price of each commodity and the price index, will be maintained into the future.

Subjectivity and a time effect are then incorporated in these distributions by allowing the grazier to specify a degree of uncertainty in the ABARE forecast. This uncertainty, which increases over time, is represented by error bounds expressed as the forecast ± some percentage. It gives rise to unique standard deviation parameters for each year and for each grazier. The mechanism involves forming symmetric triangular distributions around the estimated mean and standard deviation parameters described above, with the upper and lower bounds on the distributions being the estimate ± the specified percentage error for that year. Since these triangular distributions are symmetric, the net effect is to increase the dispersion (standard deviation) of the normal distribution but leave the mean unchanged. As noted, these errors increase over time: that is, a one year ahead forecast has a smaller standard deviation then the forecast for an interest rate two, three or four year ahead.

As with commodity prices, stochastic interest rates on financial assets and liabilities are also accommodated using the hierarchy of variables approach. Probability distributions for interest rates are based on forecasts of the top prime rate on overdrafts over $100000 provided by ABARE (ABARE 1990). These interest rate forecasts are used to obtain regression estimates for the range of interest rates included in the RISKFARM model. Each estimate and its associated standard error become the mean and standard deviation of a normal distribution, and are then adjusted to account for time effects and grazier-specified uncertainty in the ABARE forecast. This technique also requires the assumption that the historic relationships amongst the interest rates and between each interest rate and the top prime rate, will be maintained into the future

Since the forecasts for overdraft interest rates are used as an explanatory variable in estimating the regressions, it is not appropriate to apply the same procedure to obtain probability distributions for this variable Instead, it is simply assumed that overdraft interest rates are triangularly distributed around the ABARE estimate. That is, a symmetric triangular distribution is formed using the ABARE estimate as the modal value, with the percentage error margins specified by the grazier forming the upper and lower bounds.

In a recent study, probability distributions for commodity yields were elicited from the four co-operating graziers during the interviewing process. The graziers were requested to specify the minimum, maximum and most likely yields for each of the commodities produced, or planned to be produced, on their property. In addition, information regarding the likelihood of the specified minimum value actually occurring was sought. These data provided sufficient information to completely define unique triangular probability distributions for yield for each of the commodities produced. It was assumed that these distributions remained the same over the four future years modelled.

When there was a non-zero probability of the specified minimum yield being achieved, the grazier had in fact specified the parameters of a truncated triangular distribution of the form shown in Figure 4. Rather than providing a, m and b, the grazier had provided a', $P(a')$, m and b. It was necessary to calculate the value of a, and specify the entire distribution, for the stochastic sampling procedure to be carried out in @RISK. This calculation was a relatively straightforward application of the algebra of triangular distributions. The values of the sample points were then constrained so that all samples taken to the left of a' were read as a. That is, during the simulations, the shaded area to the left of a' was converted to P(a'), the specified probability of a' occurring.

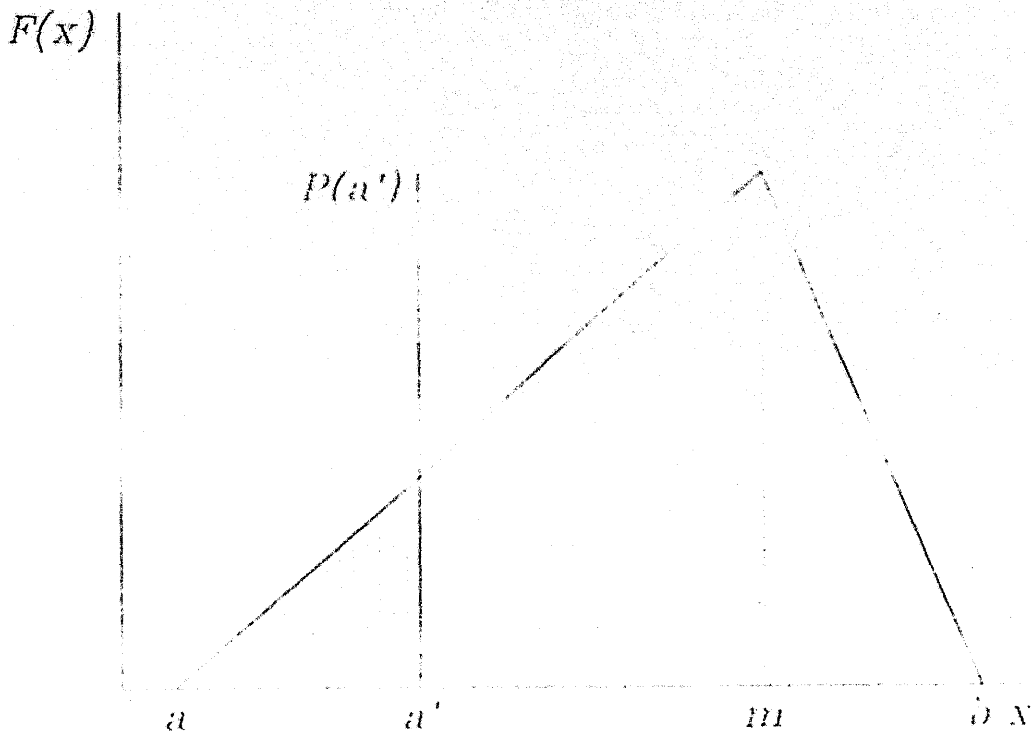
All crop yields were assumed to be contemporaneously correlated. There were assumed to be no serial correlations. The crop yield correlation coefficients used in this study were derived from national time series data. Adequate data series' at the farm-level were simply non-existent, and data at a local or even regional level were also not readily available. These coefficients thus reflect the (unavoidable) explicit assumption that the correlations evidenced in the national data were, and will continue to be, evidenced at the farm-level. Due to the averaging effects of aggregating across non-homogenous land types and disparate climatic events, these correlation coefficients probably tend to underestimate actual on-farm experience.

All livestock, livestock product and crop prices for the four future years modelled are assumed to be stochastic and correlated. No assumptions are made regarding the nature of this correlation, whether serial and/or contemporaneous, or its degree. Rather, the hierarchy of variables approach is once again used to indirectly determine and capture these correlations in the model.

The yields from animal production activities are assumed to be independent random variables uncorrelated with the yield of any other commodity. The principal variables in this category are weaning rates and per head wool cut. Crop and fodder yields are, however, assumed to be contemporaneously correlated, with the estimated correlations based on historical records. These correlations are determined empirically and are used to constrain the sampling procedure in the simulation experiments. The actual probability distributions for commodity yields on each

Figure 4

Truncated Triangular Distributions in RISKFARM



farm are determined by eliciting from each individual farmer the parameters of a triangular distribution, i.e., the minimum, maximum and most likely yields. These distributions are assumed to be the same across the four future years modelled. It is assumed that there is no serial correlation between the commodity yield variables.

Similarly to wool yields and weaning rates, livestock death rates are assumed to be independently triangularly distributed in accordance with distribution parameters specified by the co-operating graziers. These distributions are assumed to be the same in all model years.

The cost of purchased farm inputs is assumed to be independently normally distributed around a rising time trend. The time trend used is derived by regressing the agricultural prices paid index maintained by the Australian Bureau of Agricultural and Resource Economics (ABARE 1990) against time. The predictions and the standard error of the estimate from the regression model, are used as proxies for the mean and standard deviation, respectively, of the distribution of the index of farm costs. The predictions from this equation are used to index forward the cost of farm inputs recorded in the initial model year. This procedure assumes that the trend in the cost of farm inputs experienced over the period 1971 to 1990 will continue. It also assumes that the time trend, which is derived from national farm costs data, is applicable to the individual farm.

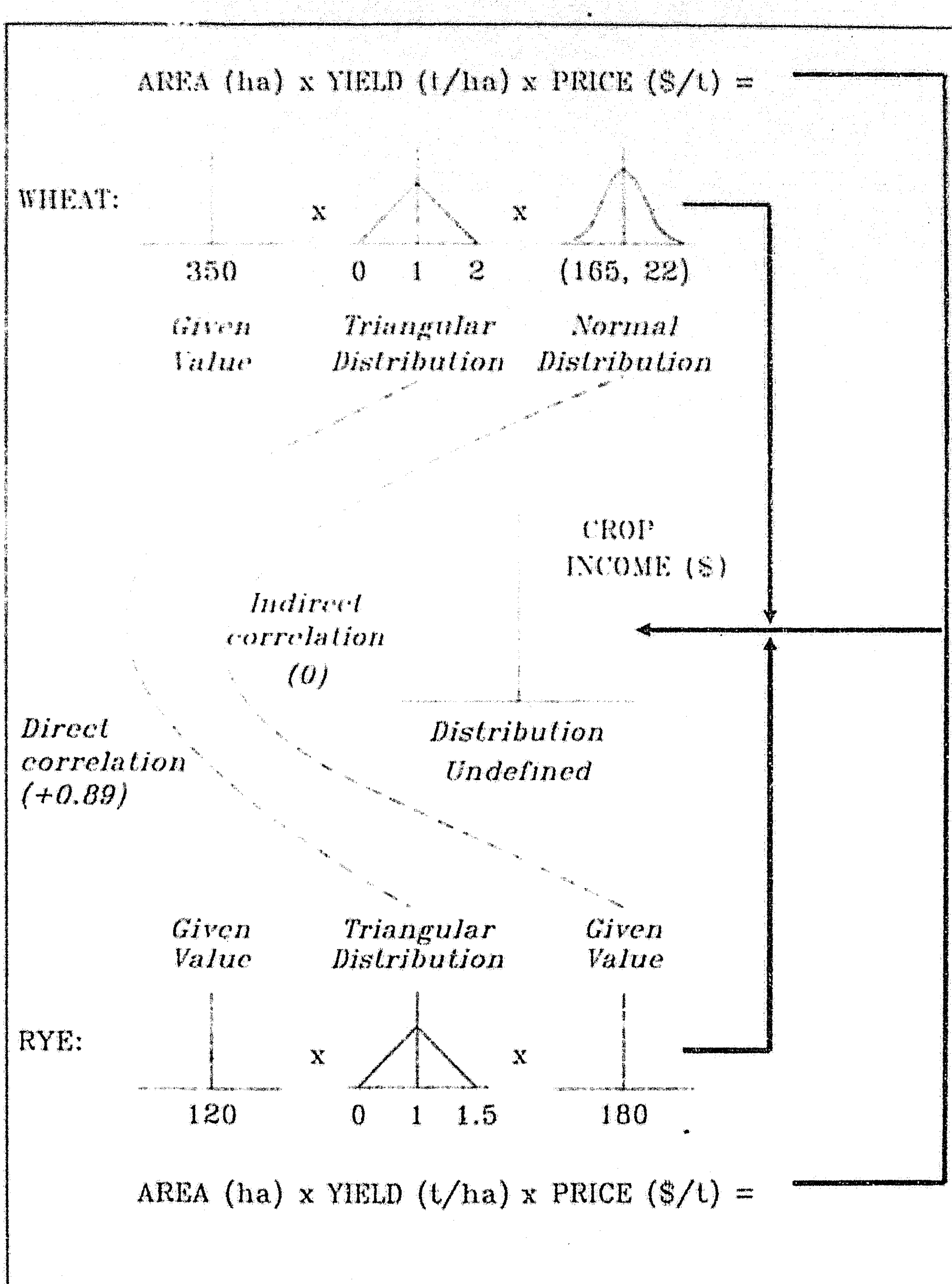
As an example of how uncertainty and risk are captured in the RISKFARM model, an actual stochastic functional relationship from a recent experiment is illustrated in Figure 5. This relationship determines the gross farm-gate income from a cash cropping activity involving the production of wheat and rye. Embedded in this relationship are four, partially correlated, stochastic variables with user-defined probability distributions (wheat yield and price, rye yield and pr[illegible] ich combine together to determine crop income. The area of each crop grown is a value speci[illegible]ied by the operator. Yields of wheat and rye are assumed to be both triangularly distributed around a mode of 1t/ha, and positively correlated with a coefficient of 0.89. Wheat prices are normally distributed around a mean of $165/t, whereas there is a guaranteed price for rye. The prices of the crops are not correlated due to this fixed price for rye output. Crop income in aggregate has an undefined distribution.

Model validation and verification

At the completion of the development phase of any modelling activity, the analyst must needs assess the ability of the model to perform the intended purpose. As noted by Anderson (1974, p.16), 'a thorough review of a model to determine if its behaviour is as anticipated during construction can be regarded simply as an essay in applied

Figure 5

An Example of Risky Cash Crop Income In RISKFARM



commonsense'. The process of carrying out such a review has been categorised into two fairly distinct steps: (i) verification, or checking the correctness of the relationships specified in the model, and (ii) validation, or deciding the adequacy of the model to mime the behaviour of the agent or system being investigated (Mihram 1972; Naylor 1971).

Verification of the RISKFARM simulation model was an on-going process carried out during and after its development. The approach taken was to divide the model into several sub-models each of which was checked and debugged in isolation using representative farm data with known production characteristics and financial outcomes. This involved degenerating all stochastic variables to values equal to the representative data and comparing the estimated outcomes with the known outcomes. This procedure was facilitated by the overall development strategy which involved: first, building a deterministic version of the model[7]; second, validating and verifying this model, and then third, modifying it to account for uncertainty and stochastic dependencies.

A second verification strategy involved checking the response of the sub-models, and the full stochastic model, against *a priori* anticipations regarding the direction and magnitude of relationships between particular levels of inputs and model outputs. The on-line visual displays of cumulative distribution functions and distribution statistics provided by the @RISK software greatly facilitated these tasks.

The concept of validation is concerned with exploring the degree of agreement between the behaviour of the model and the modelled (Anderson 1974, Naylor, Van Horn 1971). Since this must take account of the purpose of modelling, validation must be essentially subjective, and hence controversial, in application (Anderson, Naylor and Finger 1967). The problem is exacerbated when the modelling exercise involves forecasts of events, decisions and outcomes that will not actually be experienced, and thus provide validating data, until some years in the future.[8]

Since the simulation experiments carried out using RISKFARM involve estimating the outcomes of pre-specified decisions and intentions rather than forecasting outcomes based on flexible decision rules, much of the controversy over validation is avoided. Under these conditions, it is justifiable to argue that, provided the assumptions in the model are founded essentially on observed empirical regularities, which was checked and confirmed during the verification process, any other form of validation is unnecessary (Samuelson 1965). This,

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[7]This model, called FINFARM, is described in Milham, Powell and Hardaker (1992).

[8]A good example of this are the problems in validating the models of world climate being used to predict the effects of global warming (see, for example, Parry *et al.* 1988a; 1988b).

however, did not abrogate the necessity of testing the validity of the empirical approaches used in RISKFARM to approximate the correlation relationships between farm commodity prices, between interest rates and between crop yields.

Turning firstly to crop yields: The correlations between crop yields incorporated in the RISKFARM model for the simulation experiments reported in this study were based on region-level data. Due to data limitations, it was not possible to validate the accuracy of these correlations with farm-level data. While the sign on the correlation coefficients could be expected to be the same, there could be some underestimation of the degree of correlation between the crop yields actually experienced on-farm. This would result from the smoothing effects of averaging yields across a large, non-homogenous geographic region subject to patchy climatic events.

An explicit assumption in the construction of RISKFARM is that commodity yields and prices are not correlated either serially or contemporaneously at the farm-level. Statistical analysis of various yield and price data series revealed no significant relationship between these variables at the farm-level This is not surprising given the marginal contribution of an individual farm to the aggregate supply of cereal grains, wool and meat in Australia, and the open nature of the markets for these commodities. Due to time and data constraints, it was not possible to determine whether commodity yields and prices were intertemporally correlated at the farm-level. It is assumed that no such relationship existed.

It is conceivable that this assumption could lead to some bias in the model projections. However, any such bias would be equivalently reflected in all projections and, given that the experiments in this study involve comparisons of alternatives rather than the appraisal of a single project, it is reasonable to expect that the ranking of outcomes would not be much affected

As described previously, correlations in commodity prices and interest rates are captured in RISKFARM in an indirect way. The approach involves estimating individual regression equations for each interest rate and commodity price of interest. Validation of the estimated relationships was based on comparison of model predictions with the data used in the regression phase. In all cases, the actual observations lay within the 95 per cent confidence interval around the prediction. Validation on this basis, known as backward forecasting (Francisco 1980, Mihram 1972b), is less satisfactory than validating using data other than those used in developing the models, but could not be avoided due to data limitations.

Summary and Conclusion

It is argued in this paper that since farm management decisions are made in a dynamic and uncertain environment, attempts to model such decisions should also be conducted in a stochastic framework. However, as noted in the previous discussion, several practical difficulties arise in applied modelling exercises of this nature.

The first problem is to decide upon the bounds of the model and, hence, the set of single-value and stochastic variables that need to be accounted for. For example, RISKFARM contains commodity yield variables, which are described in a probabilistic form, but the stochastic variables that logically underlie those yield distributions (e.g., climatic events) are not. The second, and perhaps most major, difficulty lies in identifying and measuring dependency relationships between these stochastic variables. Alternative solutions to this problem are direct estimation of pairwise covariations or the more streamlined hierarchy of variables approach. The data collection and analysis involved in either of these can be expected to take a considerable amount of time. An issue in the application of the hierarchy of variables technique is the existence of, and availability of forecasts for, an appropriate variable to use as the independent macro-level variable.

Once the model has been constructed, the issues of verification and validation must be addressed. For large and/or complex stochastic models, the recommended approach, followed during the development of RISKFARM, is to first construct a deterministic version of the model and to then modify it to capture stochasticity. It will almost certainly prove a far less complicated matter to verify and validate the preliminary version and to subsequently recheck the modified sectors, then to attempt to validate and verify a complex stochastic model from scratch. Allowing other analysts to experiment on the model can also prove extremely valuable in the de-bugging process.

A more general issue is that of time: the time required to both develop and to operate complex stochastic models. RISKFARM, for example, took about two years to develop. Experience indicates that it also takes some three to four hours of interviewing to collect the necessary data from the farm manager; a further two or three hours to enter the data and experiment scenarios into the model; and, depending on the computer, up to half an hour per model run.

The more detailed the model, the more difficult it will be to capture all the stochastic dependencies, the more time consuming it will be to construct and run, and the more data-hungry it will be. Unfortunately, the sensitivity of the outputs of any particular model to the omission of stochasticity and dependency relationships, deliberate or otherwise, may be difficult to determine without first constructing the more complete version.

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