CRC for Weed Management Systems

Technical Series No. 2

An Integrated Economic Methodology for Evaluating the Impacts of Weeds in Agricultural Production Systems and the Farm and Industry Benfits of Improved Weed Managment.

D.T. Vere, R.E. Jones and G.R. Griffith

Established and supported under the Commonwealth Government's Cooperative Research Centres Program

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Front Cover: A dense infestation of serrated tussock in flower on right of fence, December 1995; scattered plants on left of fence. Site north of Tuena near the Abercrombie River, NSW. Photo: M. Campbell, NSW Agriculture

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An Integrated Economic Methodololgy for Evaluating the Impacts of Weeds in Agricultural Production Systems and the Farm and Industry Benefits of Improved Weed Management

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1. Introduction

Weeds cause substantial economic costs in Australian agriculture. In the inaugural newsletter of the Cooperative Research Centre for Weed Management Systems (CRCWMS), this economic cost was estimated to exceed $3.3 billion annually in terms of reduced productivity and the costs of weed control. It is significant that this cost estimate is equivalent to the average annual net value of Australian farm production over the past five years.

The costs of weeds assume a major economic importance in Australian farm production systems because of the extensive nature of most forms of agricultural production and the low yields per unit area relative to those in other developed countries. Increasing economic pressures reduce both the private and public tolerance to the effects of weeds. Weeds impose costs on producers through yield and quality reductions, the input requirements for control and in extreme weed-effected situations, the costs of adjustment to new production systems. The costs of yield reductions also have broader economic effects if many producers are affected because of possible variations in supplies and effects on product prices. Spreading weeds also impose external costs on both the farm sector and on the broader environment where the aggregate level of private weed control is less than which could be justified by society. This is where weed costs are internalised within the farm.

Estimates of the economic costs of weeds provide an economic basis for establishing the status of plants as weeds, for rationalising the weed control programs of producers and governments, and for directing weeds research programs (Vere and Auld, 1982). Despite the high annual costs of weeds in Australian farming systems, reliable estimates of these costs are difficult to find. The few estimates that have been made tend to be aggregative and highly subjective, and rarely reveal how they were derived or even what they include. Over 30 years ago, it was suggested that unlike other pests and diseases, weeds tend to be taken for granted, and are so common and widespread that their economic costs in terms of productivity losses and control inputs are not generally appreciated (USDA, 1965). This remains the case despite advances in the methods for mapping weed populations and in assembling other weed data.

Of the productivity loss and control cost components of the costs of weeds, it is likely that the former would greatly exceed the latter. Productivity in an economic sense refers to the relationship between outputs and inputs in which improved production practices enable producers to either increase outputs from the same inputs or to maintain outputs from reduced inputs. In either case, the realisation of productivity gains requires improved input use efficiency and these will be sustainable where lower production costs result. For most producers, the main options for achieving productivity gains are by the use of superior inputs and in improving the base farm resources including pastures and farm management. Improved weed control is a prominent example of a productivity-improving option.

Where the widespread adoption of new production technologies such as weed control results in productivity gains in the form of increased outputs, the competitive nature of most of Australia's rural commodity markets suggests that both consumer and producer prices are likely to be lower than those prior to technology adoption. This means that the adoption of improved weed control practices will have economic implications beyond the farm, and that an integrated economic model incorporating both the production and marketing sectors of the industry is required to accurately assess the impacts of weeds and the new weed control technologies. Farm-level models are necessary to establish the effects of weeds in production systems and the output and revenue changes from improved weed control. Such evaluations highlight the costs of weeds and provide producers with estimates of the benefits of weed control. Producers can then identify the current status of their weed management practices. Industry supply responses to improved weed control are then estimated by aggregating the farm responses under an industry adoption level to derive estimates of the overall industry benefits from reducing the impacts of weeds. Both levels of evaluation are necessary to identify the full impacts of improved weed control across an industry and to identify the options in weed research programs.

The stated goal of the CRCWMS is to reduce the costs of weeds to Australia by at least ten percent by the year 2000. The CRCWMS aims to achieve this goal by “conducting innovative research to understand and develop practical, integrated weed management systems that increase productivity and product quality, decrease costs, enhance sustainability and conserve biodiversity in natural and agricultural ecosystems”. To achieve this goal, the CRCWMS must demonstrate that the weed management systems it develops are both technically and economically feasible at the production level. Further, these technologies must also benefit society overall and not just the farming sector. The primary function of Sub-programs 1.2 and 2.2 (Economics and Decision Support) is to determine this economic information using reliable economic data and methods.

The economic approach to evaluating new technologies in weed management described in this paper is intended to address two fundamental issues of importance to the CRCWMS. The first is the need to develop a rigorous economic approach to evaluating the relative impacts of the target weeds at both the farm and industry levels. The second is the need to determine the full range of potential farm and industry benefits from the development and adoption of improved weed control practices. The achievement of both these purposes will contribute important economic information on the impacts of weeds and the benefits of improved weed control. This information will facilitate the promotion of improved weed control to producers and will assist this program’s management to make better assessments of the extent to which the CRCWMS has achieved its stated goal.

This integrated economic approach to production technology evaluation recognises the basic relationship between productivity and technology change and considers the adoption of improved weed control to be an important source of productivity gains in crop and grazing systems. Adopting this definition thereby enables the impact of improved weed control to be evaluated in terms of the productivity changes it induces[1]. This modelling system is equally suited to both the *ex ante* and *ex post* evaluation of weed problems.

The structure of the paper is to first present a brief review of the methodology of production systems modelling. This is considered to be necessary because the lack of these models represents the main deficiency in the modelling resources available to this research program. Then follow details of the farm and industry modelling methods which are adopted in the construction of the integrated model. Examples of the application of this modelling system to a hypothetical and an actual weed problem are then presented to demonstrate the procedures involved.

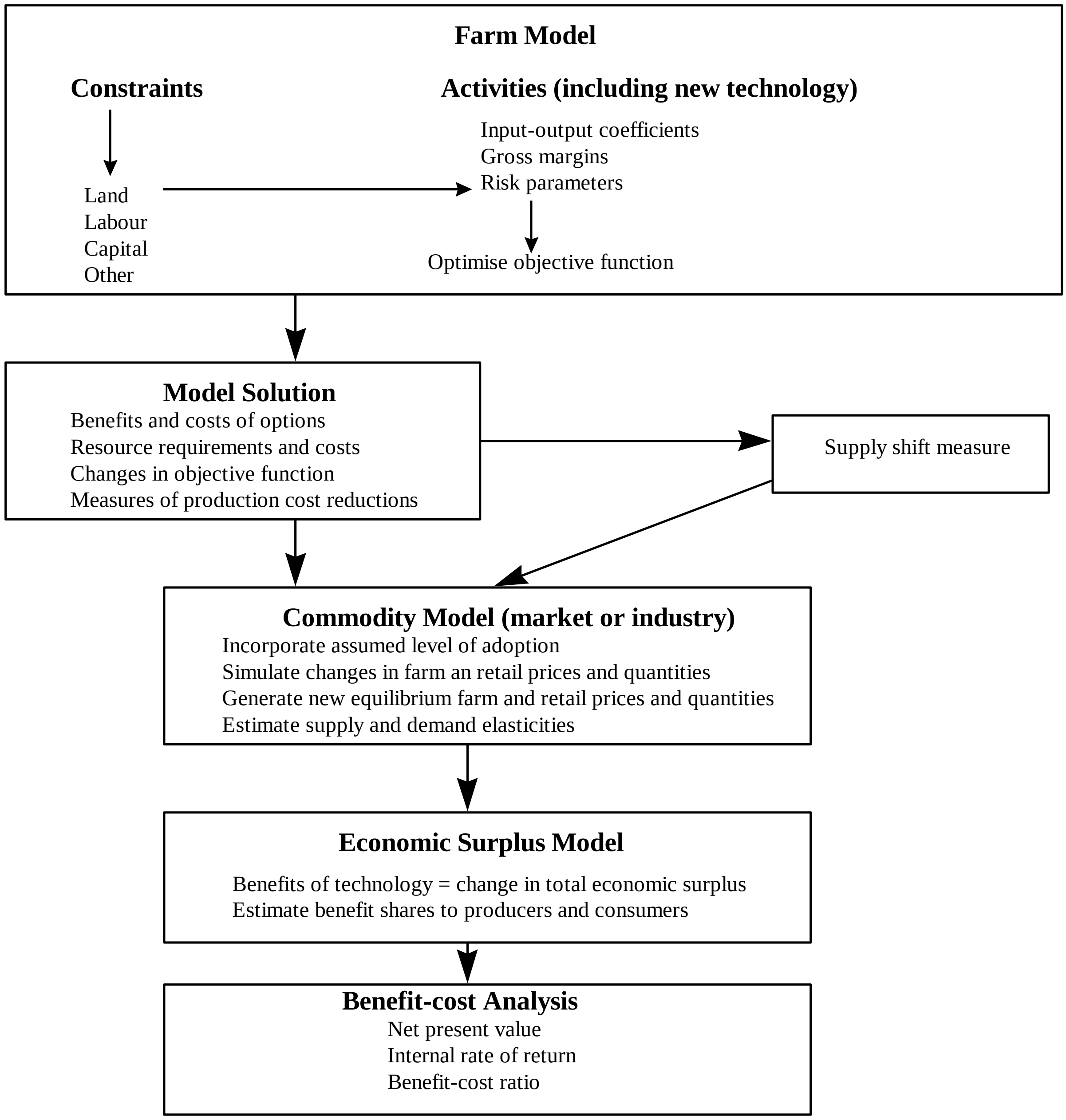
[1] All further reference to the evaluation of productivity change and technology adoption is made in the context of the impacts of weeds and their control.

2. An Integrated Economic Modelling System for Evaluating Weeds

The main components of the integrated economic modelling system for evaluating weed impacts and weed control technology are illustrated in Figure 1. This system indicates the sequence of evaluation in establishing the initial production effects in terms of the costs of production losses and the benefits of control. The market impacts are then evaluated under a known level of weed incidence or of weed control adoption throughout an industry. These estimates then allow the industry benefits to be established and the social benefit-cost criteria to be calculated.

In evaluating either the impact of a weed or the benefits of its control on a production system, this modelling system enables the with and without weed production differences to be established and these to then be translated into an industry supply change under some given level of infestation or control technology adoption. The two essential

***Figure 1**: An integrated economic model of production technology evaluation*



questions this system will help to answer are (i), what are the economic effects of weeds in production systems and how might these change with better weed control? and (ii), how might the commodity market change and what are the industry-wide economic effects? The answers to these questions determine whether the development of improved weed control is likely to be profitable from both the producer's and industry's perspectives.

3. Production Systems Models

Production systems models can be categorised as being either deterministic or probabilistic. Deterministic models are those developed under conditions of assumed certainty. The advantage of these models is that they can be developed and solved with greater ease and this enables complex production systems to be modelled and analysed. Probabilistic or stochastic models allow for the incorporation of uncertainty in the model. Although this allows for a more realistic representation of actual problems, it entails greater complexity in model development and the resulting models are often difficult to solve. In this section a range of farm modelling techniques are outlined.

Four classes of farm planning models are discussed. These are budgeting techniques, deterministic optimisation, stochastic optimisation and simulation. The choice of the appropriate model will depend upon the particular problem under investigation, and the following characteristics of a problem are important determinants of methodological choice:

- deterministic or stochastic
- static or dynamic
- optimisation or budgeting or simulation
- partial or whole farm

A problem is considered to be stochastic if important variables, such as climate and commodity prices, are uncertain and can be reported in the form of a probability distribution. If variables in a problem are uncertain and the uncertainty is expected to affect the performance of alternative strategies, a stochastic methodology should be adopted. Alternatively, if variables can be adequately described by their expected values or the uncertainty is unlikely to affect the ranking or performance of strategies, a deterministic approach is appropriate.

A static methodology is one that does not consider the temporal aspect of a problem, i.e., a discrete time period such as a season or a year. A dynamic methodology considers the intertemporal effects of a problem and is solved for a predetermined length of time[2]. If a problem requires the determination of the optimal allocation of a resource over time, or the measurement and valuation of the impact of a particular strategy for a specified decision horizon, then a dynamic methodology should be used. A range of techniques can be used to incorporate the temporal aspects of a problem. These include budgeting (cash flow analysis), optimisation (multiperiod and recursive linear programming, and dynamic programming) and simulation models.

Another consideration is whether the problem requires an optimisation methodology. These models seek to maximise or minimise some objective function of a number of possible variables. Such models will return an optimal strategy subject to the physical and institutional constraints facing the production system. Alternatively, simulation modelling seeks to conduct sampling experiments on a mathematical model of the system. Reasons for adopting simulation over optimisation models are to account for risk or where there are complex objective functions such as utility functions. However, optimisation models remain a powerful and efficient means (even when risk is involved) for determining an optimal plan or strategy from a large range of alternatives.

The final consideration is whether to evaluate the problem at a partial or at a whole-farm level. In agricultural research, optimisation models are often specified as whole-farm while particular budgeting techniques such as gross margins and partial budgets can only be conducted at a partial level. A whole-farm approach should be adopted where there are important interactions between farm resources and on-farm activities.

[2] One exception to this is infinite-stage dynamic programming which determines the optimal decision horizon for the problem. This is an advanced technique and is not dealt with in this paper.

3.1 A brief review of farm models in weeds research

The application of economic models to weed management problems has not been extensive either in Australia or other countries. Most applications have adopted an optimisation approach although there are examples of the use of simple techniques such as partial budgeting and gross margin analysis (Pannell, 1988). Benefit-cost analysis has also been used to assess the costs of weeds to Australian agriculture (Vere *et al.*, 1980; IAC, 1985), as has discounted cash flow analysis in assessing weed costs at the farm level (Campbell and Vere, 1995; Vere and Campbell, 1979, 1984; Vere *et al.*, 1993).

Of the optimisation techniques, dynamic programming (DP) and linear programming (LP) have been most often applied in Australian weeds research. Fisher and Lee (1981) used DP to solve the rotation problem faced by grain growers in New South Wales in areas where wild oats (*Avena fatua spp.*) and the disease crown rot (*Fusarium graminearum* Group 1) have a significant effect on wheat yields. Kennedy (1987) also adopted a DP approach to calculate the optimal rates of clopyralid for the control of hardyheads (*Acroptilon repens*) in Victoria. Pandey (1989) developed a stochastic dynamic programming (SDP) model to assess control measures for wild oats. Pandey and Medd (1990) used deterministic DP, linked to a bio-economic simulation model, to assess the economic feasibility of seed kill for controlling wild oats in wheat. Pandey and Medd (1991) further utilised a SDP framework, again linked to a bio-economic simulation model to analyse a continuous wheat cropping system infested with wild oats.

There are a number of examples of the application of LP in Australian weed situations. Pannell and Panetta (1986) used a whole-farm mixed integer programming (MIP) model to estimate the cost of skeleton weed (*Chondrilla juncea*) in the Western Australian wheatbelt. They considered the cost of the weed to the cropping enterprise and its benefits as a source of livestock feed. Clark *et al.* (1984) used a whole-farm LP model to assess alternative tillage practices, while Schmidt *et al.* (1994) used LP to assess the economic implications of adopting alternative management practices for the control of herbicide resistance in ryegrass (*Lolium rigidum*). Other more rigorous economic methods adopted to analyse Australian weed problems include the use of simulation for the evaluating the skeleton weed eradication program in Western Australia (Pannell, 1984) and production function analysis and calculus to determine optimal herbicide rates (Pannell, 1990).

Apart from the application of SDP by Pandey (1989) and Pandey and Medd (1991), there has been very little analysis of the effects of risk in Australian studies of weed economics. In the United States there has been some limited use of techniques which account for risk such as Monte Carlo simulation (King *et al.*, 1986) and stochastic dominance (Zacharias and Grube, 1984) in the economic analysis of weed problems. There has been greater adoption of risk techniques in the pest control literature which may be equally applicable to problems of weed management.

3.2 Budgeting methods

A range of budgeting methods can be applied in production systems analysis. The main methods are gross margins and partial and whole farm budgeting. These methods are usually static in nature, with the problems being analysed only involving short-run decisions.

Gross margin A gross margin budget is the difference between the gross income earned and the variable costs incurred in obtaining revenue for an activity. Gross margins for crops and pasture activities are generally expressed on a per hectare basis while for livestock enterprises gross margins are usually reported on a per head or dry sheep equivalent (DSE) basis. The gross margins per hectare of crops and per head of livestock are widely used in the comparative analysis of activities. Valid comparisons can only be made in terms of a production unit common to all the farms or activities being compared. Gross margin analysis is a useful first step in deciding on the best combination of activities. The procedure is to select the highest gross margin per unit of the most limiting resource and expand it until some other restraint is met. Then the activity with the highest gross margin of all the remaining available activities is introduced until it too meets a restraint.

Partial budgeting Partial budgeting is useful in assessing the likely value of introducing a new program by comparing it with the existing situation. Alternative programs are assessed only with respect to the extra income and extra cost items that are incurred. Exclusion of the common aspects of the alternative programs substantially reduces the complexity and computational effort of the analysis.

Whole-farm budgeting A whole-farm budget provides information about the expected financial outcome from a selected farm program. The usual period for developing a whole-farm budget is the forthcoming year. In a whole-farm budget, future annual operating expenses and gross income of a farm business are determined. Variable and overhead expenses are deducted from gross income to derive an operating profit, which is then expressed as a percentage return on total capital.

Cash flow development budgets Cash flow development budgeting is a form of investment appraisal and provides greater detail than a whole-farm budget by measuring the flows of cash from a selected farm program over time. Generally the capital costs of a new program are incurred initially (resulting in large cash deficits), while the benefits of the investment are accrued over time. Discounting techniques are required to convert the future cash streams to a present day value so that alternative farm plans can be compared and ranked.

3.3 Deterministic optimisation models

Models which seek to maximise or minimise a numerical function of a number of variables, with the variables subject to certain constraints, form the general class of optimisation models. Those models which do not consider uncertainty are termed deterministic. The two main classes of optimisation modelling are linear and non-linear models.

Linear programming (LP) LP is the most widely used of the optimisation techniques. It is a mathematical method for allocating scarce resources to achieve an objective such as maximising profit. LP involves the description of actual decision situations as a mathematical model that consists of a linear objective function and linear resource constraints.

The objective of an LP model is to either maximise or minimise a predetermined objective function. In farm planning problems the most common objectives are the maximisation of profit or minimisation of cost. The decision variables of the LP model denote the level of activity or quantity produced and are the activities which are to be considered in the problem. Activities include items such as the number of livestock to be carried, areas of crops to be sown, amount of fertiliser to be applied, the hours of casual labour to hire, and the amount of irrigation water required. The model's constraints are the resources available for production and these can be grouped into land, labour, capital, husbandry, legal, institutional and marketing constraints, and personal factors.

The algebraic form of the generalised LP model is given by;

$$\max\ (\min)\ Z = \sum_{j=1}^{n} c_j x_j \tag{3.1}$$

subject to

$$\begin{aligned} &\sum_{i=1}^{m} a_{kj} x_j \ (\leq, =, \geq) b_k \\ &x_j \geq 0 \end{aligned} \tag{3.2}$$

where, Z is the objective function to be maximised or minimised, x_j are the decision variables, c_j are the objective function values for the decision variables, a_{kj} are the input-output coefficients and b_k are the resource constraints. The a_{kj}, b_k and c_j parameters are assumed to be known constants.

Examples of decision variables are crop and pasture activities, livestock enterprises, casual labour hire, and the purchase of production inputs (e.g., fertilisers, irrigation water). Resource constraints include land (soil type, slope, aspect, irrigation technology), labour, capital and institutional factors (e.g., quotas). Examples of the input-output coefficients include monthly pasture dry matter production, crop yields, livestock feed energy requirements, yield responses to fertiliser application, monthly or seasonal labour and capital requirements of crop, pasture and livestock enterprises.

A number of implicit properties have to be met for the use of LP to be valid. The main requirement is that the objective function and all related constraints must be linear. Linearity implies that the model's relationships are directly proportional which means that the rate of change, or slope, of the functional relationship is constant. Therefore, changes of equal size in the value of a decision variable will result in exactly the same relative change in the functional value. Also, LP requires that the total measure of outcome (the objective function) and the total sum of the resource usage (the constraints) must be additive, i.e., the total profit (Z) will equal the sum of profits earned from each individual activity $c_j x_j$. The sum total of a resource utilised must be exactly equal to the sum of the resource used for each individual activity ($a_{kj}x_j$). Further, LP requires that the solution values for the decision variables (x_j) are not restricted to integer values. These are therefore continuous variables, compared to integer or discrete variables. Finally, the values of the parameters (c_j, a_{kj} and b_k) are assumed to be known constants. LP assumes a decision problem in a static time frame in which all parameters are known with certainty.

For many decision problems the above properties required for LP are restrictive, in particular the assumptions of linearity, divisibility and certainty. Alternative methods have been developed to accommodate these problems.

Non-linear programming (NLP) The assumption of linear relationships is often appropriate or a reasonable approximation for the range of values considered for the variables of a given problem. However, for some problems (such as when diminishing returns to scale are present) non-linear relationships or functions must be constructed in order to accurately reflect the structure of the problem. NLP models are developed to capture these relationships in either the objective function or constraint equations. The algorithms required for the solution of NLP problems are specialised iterative search procedures, with solutions being inherently more difficult and time demanding than similar size LP models. The general algebraic representation of the NLP model is similar to equations 3.1 and 3.2 with the exceptions that either of these two equations could be non-linear instead of the linear representation.

Integer programming (IP) For many problems the LP assumption of perfect divisibility is not realistic. For instance, purchasing 1.75 tractors or employing 2.3 full time employees are often not real-world options. Rounding may likely be inappropriate in these instances, i.e., to two tractors and two full-time staff, as the farm plan may become infeasible or sub-optimal. IP is a technique which can be applied to problems when one or more decision variables are required to take an integer or zero-one value. The IP model requires; (i) a linear objective function, (ii) a set of linear constraints, (iii) non-negativity conditions for the model variables, and (iv), integer value constraints for certain variables.

When the model requires all integer values for the basic solution it is a pure integer problem. If only certain variables are integers, it is a mixed integer-problem. When a problem requires only values of zero or one for the decision variables it is called a zero-one integer problem. The general form of the IP model is the same as that presented in equations (3.1) and (3.2) except that some or all the x_j variables can only take integer values.

Dynamic programming (DP) DP considers problems in which the outcome of a decision at one stage affects the subsequent results and decision at the next stage. This technique is well suited to agricultural and resource management problems in which intertemporal optimisation is important. Examples of the application of DP include the frequency and timing of input applications (fertilisers, irrigation water) to crops, determination of pesticide usage, livestock replacement options, drought feeding strategies, and determining land degradation management strategies (salinisation, soil erosion, etc.).

These terms describe the structure of the DP problem - decision, decision stage, state, transformation function, stage return function and objective function. The problem must consist of a sequence of decisions, $u_1,....,u_n$. A point in time at which a decision is made is a decision stage, often referred to as a stage. Any decision u_i made at the i-th decision stage has two consequences. First, it results in a change in the state of the system from x_i at stage i to x_{i+1} at stage i + 1. The change is expressed by the transformation function which is generally written as $x_{i+1} = t_i\{x_i, u_i\}$. Second, the decision results in a return at each decision stage given by the stage return function, $a_i\{x_i, u_i\}$. The overall objective of the problem must be to select the decision sequence $u_1,....,u_n$, so that a separable objective function of the n stage returns is optimised. The objective functions most frequently encountered are the sum of stage returns, or the present value of stage returns. This is represented as;

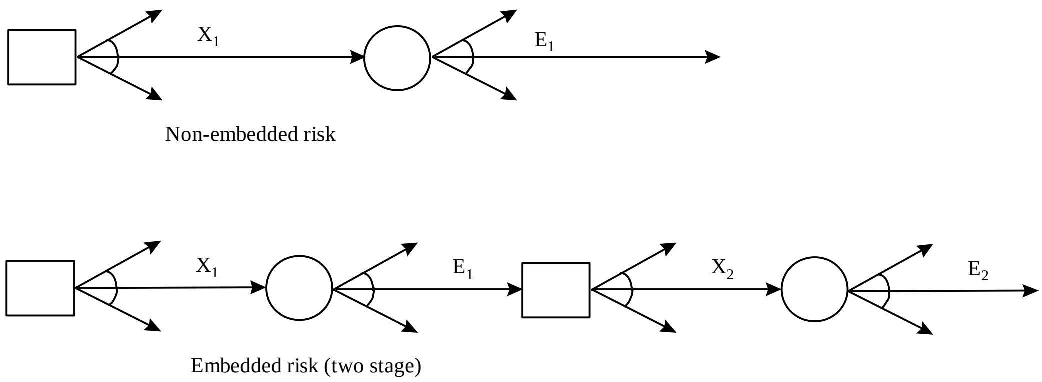
$$\sum_{i=1}^{n} a^{\,i-1} a\left\{x_i, u_i\right\} \qquad (3.3)$$

The final decision to be taken, u_n, determines the terminal state of the system, x_{n+1}. There may be some final value $F\{x_{n+1}\}$ associated with the terminal state, in which case it is included in the objective function. In summary, a DP problem with an additive objective function has the following form:

$$\max_{u_1,\ldots,u_n} \sum_{i=1}^{n} a^{\,i-1} a_i\left\{x_i, u_i\right\} + a^{\,n} F\left\{x_{n+1}\right\} \qquad (3.4)$$

subject to

***Figure 2:** Outline decision trees of non-embedded and embedded risk*



Source: Hardaker, Pandey and Patten (1991)

$$x_1 = \bar{x} \tag{3.5}$$

$$x_{i+1} = t_i\{x_i, u_i\} \qquad (i = 1, \ldots, n) \tag{3.6}$$

and any constraints on u_i.

The corresponding recursive equation for solving the problem is:

$$V_i\{x_i\} = \max_{u_i}\left[a_i\{x_i, u_i\} + aV_{i+1}\{t_i\{x_i, u_i\}\}\right] \qquad (i = n, \ldots, 1)$$

(*i*=*n*,...,1) (3.7)

with

$$V_{n+1}\{x_{n+1}\} = F\{x_{n+1}\}$$

$$x_1 = \bar{x}_1 \tag{3.8}$$

and any constraints on u_i.

3.4 Probabilistic optimisation models

A useful distinction between the types of risk faced by decision makers is provided by Hardaker *et al.* (1991) who explained that risk can be either non-embedded or embedded. The concept of non-embedded risk considers that it is realistic to model the system as if all decisions are made initially, at X_1 and that uncertainty unfolds subsequently in terms of risky consequences of the choice taken, i.e., E_1 (Figure 2). In the case of embedded risk, the decisions are segregated into those taken initially (X_1) and those taken at a later stage, (X_2) when some uncertainty (E_1) has unfolded. The second stage decisions will be conditioned by both the initial choices and the revealed risky outcomes.

Most farm decision problems involve embedded risk. However, many of the mathematical programming approaches which incorporate uncertainty do not account for this. Generally, non-embedded risk is confined to objective function coefficients while for embedded risk, both the objective function and constraint coefficients can be stochastic. Hardaker *et al*. (1991) classify models which account for risk in the objective function as ***risk programming*** models, while models which incorporate risk in the input-output or level of coefficient constraint variables are called ***stochastic programming*** models. This same convention has been used when discussing the alternative methodological approaches in the following sections on risk programming and stochastic programming.

3.4.1 Risk programming

Quadratic risk programming (QRP) The QRP approach to risk modelling adopts mean-variance (*E-V*) analysis as a conceptual framework. *E-V* analysis bases the selection of risky prospects on the means and variances of their probability distributions. In this formulation, risk is only considered in relation to activity net revenues (c_j), the constraints are regarded as being deterministic. The objective function of the QRP model is to minimise variance for alternative expected returns.

$$\min V(z) = \sum_{i=1}^{n} \sum_{j=1}^{m} s_{ij} x_i x_j \tag{3.9}$$

subject to

$$\sum_{i=1}^{m} a_{kj} x_j \le b_k$$

$$\sum_{i=1}^{n} E(c_j) x_j = l \qquad l = 0 \to E_{\max} \tag{3.10}$$

$$x_j \ge 0$$

where, $V(z)$ is the variance of profit of the current plan, s_{ij} is defined as the covariance of the per unit net revenues of activities i and j, a_{kj} is the matrix of input-output coefficients, b_k is the vector of right hand side constraints and $E(c_j)$ is defined as the expected net revenue per unit of activity j. The parameter l measures the expected profit $E(z)$ of the current farm plan for values of $l = E(z)$ in the range 0 to E_{max},, the maximum possible expected profit regardless of variance (i.e., the LP solution to the same problem).

The parameter l is varied over a feasible range parametrically to yield a set of solutions that minimise variance for given levels of expected profit. These solutions are sufficient to define the efficient *E-V* boundary. The acceptability of any particular plan to decision makers will depend upon their preference among various expected income and associated variance levels described by their individual *E-V* utility functions. As individual utility functions are often difficult to elicit, an alternative approach is to allow the individual to choose among the set of efficient farm plans.

The QRP approach requires *a priori* knowledge of the mean net revenues for each activity and the corresponding variances and covariances. A common approach to derive this information is to use time series or cross-sectional data of observed net revenues.

Minimum of Total Absolute Deviations (MOTAD)

The MOTAD formulation to risk problems was developed by Hazell (1971), and is an approximation to *E-V* efficiency which can be modelled using LP. This method closely parallels the QRP approach, but without the need for a non-linear algorithm. The concept of MOTAD is to minimise total (or negative) absolute deviations about expected income, subject to constraints on expected income and other resources. Time series data is often used in such an analysis with the unbiased estimate of mean absolute deviation (MAD) of expected profit given by;

$$M = s^{-1} \sum_{r=1}^{s} \left| \sum_{j=1}^{n} (c_{rj} - E(c_j)) x_j \right| \tag{3.11}$$

where, s is the sample size, c_{rj} is the net revenue observation for the j-th activity in the r-th year, and $E(c_j)$ is the sample mean net revenue per unit of the j-th activity. Using M as a measure of uncertainty, it is reasonable to consider E and M as the parameters in the selection of a farm plan and to define efficient *E-M* farm plans as those having minimum absolute income deviation for a given expected income level E. The formulation of MOTAD is to maximise the expected farm profit with a parametric constraint on the sum of the absolute deviations. The specification of the model is;

$$\max \quad E(z) = \sum_{j=1}^{n} E(c_j) x_j \tag{3.12}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k$$

$$\sum_{j=1}^{n} (c_{rj} - E(c_j)) x_j + y_r \ge 0 \tag{3.13}$$

$$\sum_{r=1}^{s} y_r \le l \quad = \frac{sM}{2} \qquad l = 0 \to l_{\max} \tag{3.14}$$

$$x_j \ge 0$$

where, $E(z)$ is the expected return of the solution, y_r is a measure of the deviations for each year of sample data, and l is a variable which measures expected income. l is parametrically varied to derive basis changes so that the efficient *E-M* pairs can be determined. It is then a simple matter to compute the *E-V* locus of the *E-M* efficient set of farm plans.

Hazell (1971) demonstrated that the justification of M as a measure of risk is because an unbiased estimate of the population variance is given by $M^2[ps/2(s\text{-}1)]$ when the population is normal or approximately normal. It has been shown by Thompson and Hazell (1972) that the efficient farm plans generated by this method corresponds closely with the *E-V* efficient set, and that the MAD model can be a satisfactory alternative to QRP, and may even be superior if distributions are skewed.

Utility programming Lambert and McCarl (1985) summarise a number of criticisms of *E-V* models. These relate to *E-V* assuming (i) a quadratic utility function, which implies increasing risk aversion with increasing wealth; (ii) an underlying normal distribution of wealth, whereas the real world may be characterised by asymmetric distributions; (iii) small risk relative to wealth, whereas some situations do not involve risks which are small; and (iv) that *E-V* solutions are a reasonable approximation to the expected utility solutions. They proposed a NLP model called direct expected utility maximising non-linear program (DEMP), as an alternative to *E-V* models. Two formulations were proposed, one based on NLP and the other based on separable (but still nonlinear) programming. These formulations are;

Formulation A:

$$\max \sum_{k=1}^{n} p_k U(w_o + c_k x) \tag{3.15}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k$$

$$x_j \ge 0$$

Formulation B:

$$\max \sum_{k=1}^{n} p_k U(w_k) \tag{3.16}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k$$

$$c_k x - w_k = -w_o \qquad k = 1,2,\ldots.,n \tag{3.17}$$

$$x_j \ge 0, \quad w_k \ge 0$$

where, p_k is the probability of the *k*-th state of nature occurring, w_o is initial wealth, c_k is the vector of net wealth contributions per unit of *x* under the *k*-th state of nature, $c_k x$ is the increment to wealth under the *k*-th event, thus $U(w_o+c_k x)$ is the utility obtained from the wealth level achieved under state *k* with decision *x*. The principle restriction on the DEMP model is that the utility function be quasi-concave. Since this implies risk aversion, the restriction is tolerable. Importantly, there are no restrictions on the underlying distributions of the utility function and risk attitudes can be specified to exhibit decreasing, constant or increasing risk aversion with respect to changing levels of wealth.

Pannell (1988) and Patten *et al*. (1988) proposed utility-efficient programming (UEP) which extends Formulation B of the Lambert and McCarl specification to solution by LP. This involved approximating the utility function with linear segments. Adopting Pannell's approach, each linear segment requires an activity (U_i) and the function as a whole requires one 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. The formulation of the model is;

$$\max \quad \sum_{k=1}^{n} p_k u_k U_k \tag{3.18}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k$$

$$-c_k x + w_k U_k \le w_o \tag{3.19}$$

$$iU_k \le 1 \qquad k = 1,2,\ldots.,n \tag{3.20}$$

$$x \ge 0, U_k \ge 0$$

where, U_k is a vector of variables for the *k*-th state, u_k and w_k are m x 1 vectors of utility and wealth coefficients respectively for the *k*-th state, and *i* is an m x 1 vector of ones. A range of utility functions can be used with two examples given below. The first function has constant relative risk aversion and decreasing absolute risk aversion, while the second has constant absolute risk aversion.

$$U = a + bW^{(1-R)} \tag{3.21}$$

$$U = 1 - e^{-AW} \tag{3.22}$$

where, *U* is utility, *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.

3.4.2 Stochastic programming

Discrete stochastic programming (DSP) DSP was first formulated by Cocks (1968) and advanced by Rae (1971a,b) as a means of LP to analyse multistage stochastic problems in which the optimal activity in one period depends on events in past periods. This method has emerged as a popular approach for accounting for embedded risk in an optimising framework. DSP offers a framework where any or all of the c_j, a_{kj} and b_k elements of a mathematical programming model can be random. Discrete parameter values or states of nature are used to represent the range of possible coefficient values. DSP also captures the flow of information to the decision maker about the values of the objective function and constraint set parameters and matches that flow of information to the sequences of decisions to be made (Apland and Hauer, 1993). This is done through the specification of decision stages in which decisions are made.

Problems of dimensionality and large matrix size were noted in early applications of DSP (Cocks, 1968; Rae, 1971b; Trebeck and Hardaker, 1972). Apland and Hauer (1993) consider that these technical problems have now been overcome as "… the range of model sizes suggests that for many applications of DSP, analysts have found the desired level of model performance well within the capabilities of current mathematical software". Despite these developments, the problems associated with verifying and validating large models, which invariably accompany DSP, remain a deterrent to its use (Hardaker *et al.*, 1991).

The 'Distribution Problem' approach Johnson *et al.* (1967) developed a stochastic programming approach based upon the standard deterministic LP. In the LP model at least one of the elements c_j, a_{kj} or b_k is a random variable. If the random variable is observed before the selection of the decision vector, then the resulting problem to be solved is a deterministic LP problem. The model becomes;

$$\max f(c_j, a_{kj}, b_k) = \sum_{j=1}^{n} c_j x_j \tag{3.23}$$

subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k$$

$$x_j \ge 0$$

Since at least one of the elements of c_j, a_{kj} or b_k is a random variable with a specified distribution function, $f(c_j, a_{kj}, b_k)$ will also have an associated distribution function. A set of variates drawn from probability distributions for the random elements in c_j, a_{kj} and b_k is substituted for stochastic parameters in the problem. Letting the non-stochastic components be c_j^*, a_{kj}^* and b_k^* then the value of the criterion function in the solution to the associated deterministic LP problem $f(c_j^*, a_{kj}^*, b_k^*)$ is a variate from the probability function $f(c_j, a_{kj}, b_k)$. By repeating the procedure the distribution function for $f(c_j, a_{kj}, b_k)$ can be approximated. Johnson *et al.* (1967) define this procedure of finding the distribution function as the 'distribution problem'. A number of solutions of the LP problem are required to approximate the distribution function, the number depending upon the precision with which $f(c_j, a_{kj}, b_k)$ is to be approximated.

Recent developments in spreadsheet based optimising software and risk analysis (such as What's Best!™ and @RISK™) applications means that this approach can be solved more efficiently than when first proposed. For example, Jones *et al.*, (1994) adopted this approach to solve a large multiperiod LP model of drainage recirculation using a significantly larger number of iterations than that by Johnson *et al*. (1967) in their example (300 compared to 20).

The Johnson *et al*. methodology is essentially passive in nature, that is, all the random variables are known at the beginning of the planning period. Thus the sequential decision process is limited to two decision stages, the period when the initial strategic decisions are made and a period following when the states of nature become known when tactical decisions are made. This passiveness can be overcome (if necessary) by allowing the simulation component of the model to make additional tactical adjustments to the LP solution as further states of nature become known.

Stochastic dynamic programming (SDP) In a SDP problem, the objective function is often specified as the present value of the expected stage returns. Objective functions which include the decision makers risk preference can also be specified. Let the random variable at stage *i* which affects the transformation and possibly also the stage return, be independent and denoted by r_i. For a discrete formulation, r_i is limited to a domain of *m* values. Allow the domain of r_i to be mapped into k_i, the range of integers 1 to *m*. The probability that r_i take the *k*-th discrete value in its domain is denoted by $p_i\{k_i\}$. Instead of referring to r_i as the value of the random variable, it is convenient to refer to k_i for the purposes of describing the stochastic process.

Suppose the state of the system at stage $i + 1$ and the stage return at stage i depend on z_i, u_i and k_i only. The stage return and state transformation functions can be respecified as $a_i\{x_i, u_i, k_i\}$ and $t_i\{x_i, u_i, k_i\}$, respectively. If the objective function for a problem is the expected present value of stage returns the recursive equation for the SDP problem is;

$$V_i\{x_i\} = \max_{u_i}\left[\sum_{k=1}^{m} p_i\{k_i\}(a_i\{x_i, u_i, k_i\} + aV_{i+1}\{t_i\{x_i, u_i, k_i\}\}\right] \quad i = n, \ldots, 1 \tag{3.24}$$

subject to

$$\sum_{k=1}^{m} p_i\{k_i\} = 1 \tag{3.25}$$

with

$$V_{n+1}\{x_{n+1}\} = F\{x_{n+1}\}$$

Recursive solution of the first term results in the determination of $V_i\{x_i\}$ and the optimal decision vector $u_i^*\{x_i\}$ for $i = n$ to 1.

3.5 Simulation modelling

Not all problems lend themselves to mathematical modelling and solution in a manner that results in optimality. An alternative is simulation which is a means for deriving measures of performance about a complex system by conducting sampling experiments on a mathematical model of the system over time. The model of the system includes the relevant components of the system along with their mathematical relationships. The process of simulation normally involves computing the model in order to obtain operational information. The output of a simulation model is in the form of system descriptors which describe the behaviour of the simulated system. Since simulation of a model is similar to conducting sampling experiments on the real system, the results obtained are sample observations or sample statistics.

A characteristic of systems that often results in models being too difficult to solve analytically is the inclusion of certain system components that must be represented as random variables. These random variables are represented in the simulation model as probability distributions and the resulting model is referred to as a stochastic simulation model. Monte Carlo programming has been advanced by Anderson (1975) as a realistic alternative to mathematical programming in accounting for risk. In this approach the planning problem is set out in a similar fashion to that of mathematical programming methods but portfolios of activity levels are selected at random. These portfolios are first tested for feasibility and then evaluated in terms of some specific objective function. The procedure is one of search with a large number of portfolios being sampled. An advantage of this approach is that almost any form of objective function can be applied (linear or non-linear) and utility functions can be defined. Monte Carlo programming is particularly useful to problems when risk is non-normal and when the extent of farmers' risk aversion is unknown.

3.6 Information requirements for farm planning models in weed research

A considerable amount of biological and physical information of the production systems under review are required to develop farm planning and bio-economic models. This information can be categorised as being either resource endowments, input-output coefficients, cost and returns, and crop and farming systems. Some of the data to be obtained will be in the form of point estimates while other data, for random variables, will be required in the form of distributions. The main types of data in the resource endowments category are the basic physical constraints of the research problem. Examples include the size of the representative farm or paddock, depending on the scale of the analysis[3], soil types, irrigation technologies, availability of labour and capital, and institutional restrictions such as production quotas.

Input-output coefficients represent the bulk of the data requirements and generally are the most demanding in terms of biology and physical attributes. Particular data needs for weed research will include yields of pasture activities (daily dry matter production) and grain crops (tonnes per

[3] Some studies may be undertaken at a per hectare level.

hectare) without weeds and the yield loss relationships for different crop-weed densities. Estimates of the relationship between seed banks and weed densities are also required for different weed species, a range of crops, different geographical locations and soil types. Other important information required by these models is the effectiveness upon yield loss of alternative control agents, whether they are chemical, mechanical or biological. Examples of other input-output coefficient data include feed energy requirements of livestock (e.g., metabolisable energy per cow, ewe or DSE), response functions to different inputs (e.g., fertilisers), evapotranspiration demands, labour requirements per unit (hours per hectare, head, DSE, bale, tonne etc.), fodder feed energy equivalents (e.g., metabolisable energy per hectare, per bale or per tonne), and seasonal or monthly pasture transfer efficacy.

The cost and return data are associated with each of the decision variables, or enterprises, of the model. Most of these data are specified in the form of gross margins and variable costs on a hectare, tonne, ewe, cow and bale basis. Where there are investment activities (e.g., land purchase, irrigation technology, headers, spray equipment and hay and silage making equipment) these data must be specified at either their capital value in the year of acquisition in a dynamic or multiperiod framework or amortised, using the term (years) and interest rate that is applicable, in a static framework. For some problems that require a risk analysis, a time series of cost and return data may need to be developed.

The crop and farming systems data required generally indicates whether the problem requires an analysis of rotations, where there are multiple choices among crops, pastures and livestock, or single commodity or monoculture. This will sometimes be governed by the scale of the study as determined by the resource availability, i.e., a representative farm versus a single paddock or hectare analysis. The crop and farming systems data should comprehensively cover the detailed interactions that occur between crops, pasture and livestock enterprises.

4. Industry Models

The methods detailed in this section are applicable to evaluating the impacts of weeds where they cause opportunity costs in terms of production foregone, and to the benefits of their control where these are equivalent to the production losses prevented. In both instances, evaluating the costs of weed-constrained production and the benefits of production increases from reduced weed impacts follow the association between productivity and technology change where productivity changes can be directly attributed to adoption or non-adoption of weed control technology.

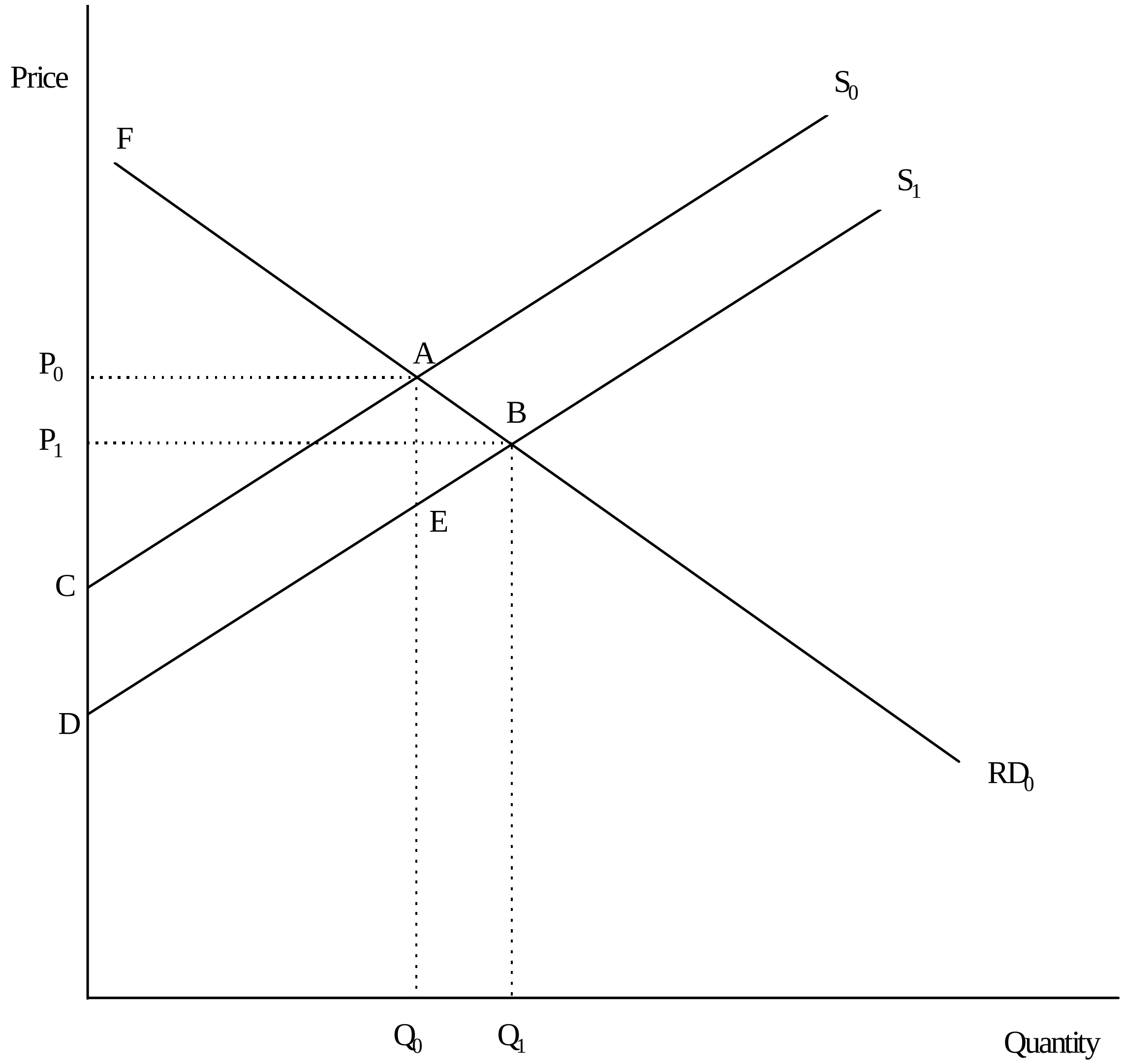
Industry level evaluations are necessary because production systems models rely on the assumption that output prices are not affected by the changes in resource allocation or product mix. This may be realistic when one farm is considered since changes in its output will rarely affect market price. However, when improved weed control technology is expected to be widely adopted in an industry, the sum of all individual farm changes will very likely lead to a change in the price of the output.

The concept of economic surplus has been widely used to evaluate the industry effects of production constraints (such as weeds) or from the adoption of production-increasing technology (such as improved weed control). Economic surplus comprises two elements, (i) consumers' surplus, which is the difference between the benefits from consuming a product and the costs of obtaining it, and (ii) producers' surplus which is the difference between the returns and costs of production. Two general situations can be identified in which the economic surplus approach is relevant in evaluating production impacts resulting from the presence of weeds or from their control. As a simplification, this discussion considers the latter situation, although it is equally applicable to the former.

4.1 Schematic economic surplus method

This method considers that weed control results in an outward shift in the supply curve for a particular product such as wool or wheat, with the demand curve remaining stationary. With information about the slopes (elasticities) of the supply and demand curves for that product, the nature of the supply shift following weed control,

Figure 3: *Effect of supply shift in a commodity market*



and the relationship between producer and consumer prices, the impact of widespread weed control on a particular industry can be evaluated. This situation is illustrated in Figure 3.

Initial production is Q_0 for which consumers pay a price of P_0. Producers have an economic surplus equivalent to P_0AC while consumers' surplus is the area P_0AF. The main economic effect of weed control is to reduce per unit production costs and shift the commodity's supply curve outwards to S_1, resulting in more output at a lower price. Here, the demand curve RD_0 remains stationary since the additional production faces the same demand as all other product. The area of economic surplus is now *FBD* comprising consumers' and producers' surpluses of P_1BF and P_1BD, respectively.

These areas of total economic surplus change represent the impact of weed control on both consumers and producers. The net change in economic surplus is equivalent to the benefits of control and this is given by the area *CABD*, the difference between the areas *FAC* and *FBD*. The incremental benefit area (*CABD)* incorporates the production cost reductions for the initial output Q_0 (the area *CAED*), and the value to consumers of the extra production at S_1, net of production costs (the area *ABE*). Where the supply curve shift is parallel so that the vertical distance between the two supply curves is constant, and following Alston (1991), the changes in the economic surplus areas from weed control can be estimated as;

Change in consumers' surplus;

$$\Delta CS = P_0 Q_0 Z(1 + 0.5Zh) \quad (4.1)$$

Change in producers' surplus;

$$\Delta PS = P_0 Q_0 (K - Z)(1 + 0.5Zh) \quad (4.2)$$

Change in total surplus;

$$\begin{aligned}\Delta TS &= P_0 Q_0 K(1 + 0.5Zh) \\ &= \Delta CS + \Delta PS\end{aligned} \quad (4.3)$$

where, P_0 and Q_0 are the initial equilibrium market-clearing price and quantity for the commodity, Z is the percentage reduction in price arising from the supply shift defined as $Z = K\varepsilon/(\varepsilon+\eta)$, K is the initial vertical supply shift expressed as the percentage reduction in production costs from the adoption of the new technology, and ε and η are the product's price elasticities of supply and demand. With estimates of these parameters, the economic surplus equations can then be solved.

The economic surplus-industry impact analysis situation represented by these formulae are applicable in any situation. The main problem is that the major industry parameters that are required by the formulae (e.g., product supply and demand elasticities) have to be obtained externally and thus they may not realistically represent the system being evaluated. A further limitation is that the static nature of this approach makes it difficult to take account of the time path of the responses of producers to improved weed control.

In evaluating either the impact of a weed or of its control on a production system, this methodology enables the with and without weed production differences to be established and these to then be translated into an industry supply change under some given level of infestation or adoption. The two essential questions this system will help to answer are (i), what are the economic effects of weeds in production systems and how might these change with better weed control? and (ii), how might the commodity market change and what are the industry-wide economic effects? The answers to these questions determine whether the development of improved weed control is likely to be profitable from both the producer and industry perspectives.

4.2 Industry (econometric) model-economic surplus method

This method applies where a quantitative industry model is available to predict new equilibrium prices and quantities following weed control. It involves simulating the impacts that weeds and their control have on the main variables (supply, demand and prices) and translating these into measures of economic surplus change.

Two types of industry models which have been used in technology impact evaluations are the structural econometric model and the linear elasticity or equilibrium displacement model. The integrated evaluation system described here utilises the structural type of model which is specified as a system of equations representing the inventory or breeding capacity, production, consumption, and price determination processes of the industry (see Appendix). The industry is specified as a set of behavioural relationships and identities and the elasticity values are obtained from the estimated relationships. The model solves simultaneously and generates equilibrium values for the set of endogenous variables.

This type of model is particularly useful in the weeds impact evaluation context because it is specifically designed to incorporate the economic fundamentals of the industry and the influences of external factors in explaining how past economic decisions were made so that these decisions might be predicted into the future. The expectation is that a model which has been properly estimated and validated over historical data will provide a sound basis for weed impact evaluations, given that the underlying industry structure is not expected to undergo substantial future change. However, it is important that the model be regularly re-estimated and re-validated so that it represents the most recent expression of the industry's economic relationships[4].

[4] At present, there are several structural econometric livestock industry models available for use in the CRCWMS evaluation program. Models of the New South Wales lamb and the Australian lamb, beef and pig industries have recently been revised and re-estimated. The Australian lamb industry model is described in the Appendix. All four models have now been incorporated in an integrated livestock industry model which will allow the cross-industry effects of weed control adoption in one industry to be directly evaluated. This can be done following the procedures which are described in Section 6. The major deficiency in this inventory is the lack of models of the wool and grains industries. Grains models are intended to be developed under the bio-economic sub-programs.

Econometric impact simulation In simulating industry impacts using a structural econometric model, particular parameter values are altered to reflect the new technology, the model re-solved, and the results compared with the base model solution. Any changes in prices and quantities are assumed to be attributable to the imposed changes resulting from technology adoption. These price-quantity changes are then converted into measures of economic surplus change. The main advantage of econometric simulation is that the dynamic responses to technology adoption can be traced out over time as the model solves period by period.

Under this method, the industry model defines the initial industry equilibrium quantity (Q_0) and price (P_0), which together define point *A* (Figure 3), the changed quantities and prices Q_1 and P_1, which together with the elasticities of demand (η) and supply (ε) for the product, and K, the vertical shift in the product's supply function, define point *B*. Here, the model can be solved to determine the equilibrium prices and quantities and simulation experiments can be conducted to examine the effects of weed control on these variables. This enables the resulting changes in economic surplus to be determined. The economic surplus formulae in this situation differ from those in the first because they are based on the simulated price and quantity changes rather than on assumed parameter and initial equilibrium values, and are given as;

Change in consumers' surplus;

$$\Delta CS = -P_{0R}Q_{0R}EP_R\left(1+0.5EQ_R\right) \tag{4.4}$$

Change in producers' surplus;

$$\Delta PS = P_{0F}Q_{0F}\left(EP_F - K\right)\left(1+0.5EQ_F\right) \tag{4.5}$$

Change in total surplus;

$$\Delta TS = \Delta CS + \Delta PS \tag{4.6}$$

where, the subscripts $_R$ and $_F$ relate to the retail and farm levels of the industry respectively, and the parameters EP_R, EP_F, EQ_R and EQ_F are the relative changes in retail and farm prices and quantities which are derived from the model simulation solutions.

The main difference between the two methods is that in the first, an initial market equilibrium is given and the given supply shift and industry parameters determine the new equilibrium price and quantity. Economic surplus is measured as a shift away from the initial point. In the second, the econometric model predicts the new prices and quantities and economic surplus is measured as a shift towards the new equilibrium. The first approach is easier to implement, but the second is more reliable if a quantitative market model is available. Irrespective of what calculation method is used, economic surplus provides a recognised measure of the likely benefit levels and their distribution from technologies such as weed control. Both of these aspects are important considerations in planning and managing the technology-generating research process in improving weed control.

When the program costs are considered, the levels of estimated benefits can be projected over time and discounted to present day values to yield the social investment criteria, net present value, benefit-cost ratio and internal rate of return. Similarly, the relative benefit shares provide guidelines for determining the appropriate equities in the sponsorship of the technology-generation process, whether by producers through their contributions to industry research funds, or by consumers through publicly-funded research.

Three considerations are important in applying the economic surplus approach in a weed control evaluation context. These are (i), the extent of the supply shift from weed control, (ii) the effects of different levels of adoption of a particular control technology on an industry, and (iii) the time path of adoption of the control technology within the industry.

Measuring the supply shift from weed control The extent of the supply shift for a particular product is a major factor in determining the levels of these benefits. Following weed control, the supply shift parameter (*K*) in the producer surplus equations (4.2 and 4.5) is measured in terms of the resulting production cost reductions. *K* can be measured in two ways. It can be derived directly from the farm model solutions as the percentage reduction in the marginal unit cost of production for the weed-affected and weed-free systems, expressed as a proportion of the product's farm price (this is a proportional supply shift).

Alternatively, *K* can be derived from a production or cost function where it is considered that the components of technical change are important. Specifically, this method allows the incorporation of the effects of both neutral technical change, where the technology results in a shift in output from the same mix of inputs and their proportions, and biased technical change which occurs where production shifts are due to a change in the input mix which biases the use of one input against others. An example of neutral technical change is where crop production increases from the use of better fertilisers although input mix proportions remain unchanged. Similarly, biased technical change might result where more chemicals are used with fertiliser use held constant.

The second method might sometimes be preferred because it conforms more closely to production economics theory. If K is to be determined from a production function, the first requirement is to convert the estimated biological effects of weed control on yield into an equivalent shift in the initial supply curve S_0 in Figure 3. This is given as the difference in the marginal costs of production between the weed-affected and weed-free systems. The translog is a useful functional form which can be used to estimate these changes. This function explicitly accounts for the separate inputs and their interactions in determining output, and has often been used to measure productivity changes from the adoption of new technologies.

The basic form of the translog production function for a single output (Q_1), inputs such as land, labour and chemicals (X_i), and a time trend (T_1) as an exogenous shifter representing production technology improvements, is given (in logarithms);

weed-constrained situation. This function can be estimated from given values for inputs and outputs, or from time-series or cross-sectional data relating to an industry within a region or state.

To determine the marginal cost differences between the two systems, equation (4.7) can be converted into an equivalent total cost function (equation 4.8) and differentiated with respect to output (Q_1) to establish the marginal costs of production.

In equation 4.8, W_i are the input prices and the remaining parameters are defined as before, recognising the incorporation of quantity (Q_1) in the cost function and its interactions with the inputs and time. The difference in the marginal costs of production between the two systems when expressed as a proportion of the farm price then provides the estimate of the supply shift that can be attributed to weed control. This measure incorporates the input level effects and those of the time trend parameters representing independent technological change. Other research has demonstrated methods for disaggregating technology improvements into their neutral and biased components (Lemieux and Wohlgenant, 1989).

$$\ln Q_1 = \ln a_0 + \sum_i a_i \ln X_i + \frac{1}{2}\sum_i \sum_j a_{ij} \ln X_i \ln X_j + f_1 T_1 + \frac{1}{2} f_{11} T_1^2 + \sum_i \sum_1 h_{i1} \ln W_i T_1 \qquad (4.7)$$

$$\ln TC = \ln a_0 + \sum_i a_i \ln W_i + \frac{1}{2}\sum_i \sum_j a_{ij} \ln W_i \ln W_j + f_1 T_1 + \frac{1}{2} f_{11} T_1^2 + b_1 \ln Q_1 + \frac{1}{2} b_{11} \ln Q_1^2 + \sum_i \sum_1 r_{i1} \ln W_i \ln Q_1 + \sum_1 \sum_1 c_{11} T_1 \ln Q_1 + \sum_i \sum_1 h_{i1} \ln W_i T_1 \qquad (4.8)$$

where, the parameters a_{ij} represent the coefficients of the inputs and their interactions, ϕ_1 is the coefficient of the time trend, and η_{i1} are the coefficients of the input and time trend interactions. The first differential of this function ($\partial \ln Q_1/\partial X_i$) yields the marginal product of each input, while the direction (ϕ_1) and rate of change (ϕ_{11}) due to advances in technology is given by ($\partial \ln Q_1/\partial T_1$). Note that while production technology improvements can result over time even if weeds significantly constrain production (e.g., from neutral technical change), improved weed control is expected to both increase production and reduce unit production costs. Hence, technical change following weed control will have both a positive direction and a higher rate of change than in the

Measuring the rate of adoption for weed control technology Estimating the adoption rates of a new weed control technology defines the part of the industry most likely to be affected by its introduction. *Ex ante* adoption rates are more difficult to estimate because the technology is usually not at the point of release to the industry. In *ex ante* situations, adoption rates are often expressed in terms of either the number of producers expected to adopt improved weed control or the number of production units likely to be affected. These can be established by elicitation methods (asking researchers and industry experts to nominate adoption scenarios), and are most conveniently expressed as changes in the level of production, i.e., controlling a certain weed is likely to increase average production by some proportion. This can then be converted into an adjustment factor to the equilibrium production level for use in the econometric simulations. Adoption rates measured in these terms are usually sensitised according to various criteria. In *ex post* analyses, adoption rates can be more directly measured through surveys and other methods.

Incorporating the industry's time path of adjustment This consideration recognises the time required for improved weed control to be absorbed into an industry. It is important because it directly affects the time flow of benefits from technology adoption, and this in turn affects the benefit-cost comparisons through the discounting procedures because the discounted values of the net benefits diminish over time. This means that technologies which are rapidly adopted are likely to have greater long term payoffs that those with longer adoption profiles.

The effects of different technology adjustment periods can be examined by simulating the impacts of the weed or control technology over different sub-samples within the econometric model's estimation sample period. For example, the effects of quick adoption might be simulated over one year and over several years where adoption is based on longer lags. This is likely to produce different sets of equilibrium prices and quantities, different levels of change in economic surplus and hence, different benefit-cost criteria when the benefit flows are discounted over time.

5. Benefit-Cost Analysis

Benefit-cost analysis (BCA) is the commonly adopted method for comparing weed control options where they involve different flows of costs and returns over time. BCA is a method of comparing the economic merits of weed control options where time and the effects of risk are important considerations. This is most likely to be where weed impacts and the requirements for control carry over time, such as in the case of residual weed problems in crops and most perennial pasture weeds.

BCA is based on discounting procedures which must be utilised to account for declining monetary values when the flows of benefits and costs are projected over the time required for weeds to be effectively controlled. The discount rate is a measure of the cost of inflation and can be expressed in either nominal or real terms. Choice of the discount rate is arbitrary but it basically needs to reflect the perceived riskiness of the weed control investment. Higher discount rates reflect riskier weed control situations.

These procedures apply equally to evaluating the farm and social benefits of weed control. In either context, applying discounting procedures allows the main BCA criteria to be calculated. These are benefit-cost ratio (BCR), net present value (NPV) and internal rate of return (IRR). The BCR is the ratio of discounted benefits to discounted costs and indicates the potential return per $1 invested. A BCR greater than one represents a profitable investment. NPV is the present day value of the discounted benefits less the discounted costs over the length of the control period. NPV will be greater than zero for a control option yielding positive net discounted benefits. The IRR is the discount rate which equates discounted benefits and costs over time, i.e., the discount rate at which NPV = 0.

The main differences between farm and social BCA's concern the measurement of the benefit-cost items and the selection of the discount rate. Wherever possible, benefits and costs should be valued at current market prices as this allows their direct comparison over time. Farm-level BCA's are usually straightforward in this regard. Difficulties may arise in the social context where the BCA requires measurement of all monetary benefits and costs and those for which market prices do not exist or are difficult to establish under normal pricing methods. Valuing environmental benefits and costs from weeds on public lands is an example in which non-market pricing methods have to be adopted. Social rates of discount are usually lower than private rates because the social investment considerations that the discount rate is required to reflect (such as risk preference and opportunity cost of capital) are generally considered to be lower than those for individuals.

In this integrated modelling system, the BCA is the endpoint of the evaluation for a particular weed. This will usually be a social BCA in which the benefit estimates are derived from the economic surplus model component and the costs are those of the research program for the weed in question. As indicated in the following section, the costs of control in the production system are accounted for in the industry's supply curve.

6. Simulating the Economic Impacts of Weeds in Production Systems

In this section, two examples are given to demonstrate the methods involved in the economic evaluation of weed problems in production systems. These are intended to demonstrate the potential benefits of using the methods described in the preceding sections, where weed control involves direct interactions between farm resources over time and market effects from supply increases.

The first example describes an application of mathematical programming-econometric methods in evaluating the farm and industry impacts of a weed in a production system. This example is hypothetical since it is not based on actual experimental data. It illustrates the economic effects of a pasture weed problem and traces the cost from the farm level to the broader community using a combination of LP, econometric modelling and economic surplus analysis. The second example utilises the results of research by Medd *et al.* (1995) and demonstrates the development and use of a bio-economic model involving the population dynamics of wild oats. In this example the benefits of alternative management strategies for controlling wild oats are assessed.

6.1 Example 1

This example considers the effects of Paterson's Curse in an irrigated sub-clover pasture in the Murrumbidgee Irrigation Area. It is assumed that the impact of Paterson's Curse is to reduce dry matter production by 20 percent.

<u>Farm model analysis</u> The model farm is 250 hectare of a red-brown earth soil type. The farm is fully irrigable and the irrigation technology is flood irrigation on landformed contour bay and non-landformed contour bay layouts. Approximately 70 percent of the farm is laser controlled landformed and the irrigation allocation is 1,400 megalitres annually with a water delivery constraint of 550 megalitres per month. A single owner-operator contributes 56 hours of labour per week to the farm operation. This labour supply is converted to a seasonal equivalent in the model.

The main agricultural activity is second-cross lamb production which utilises lucerne and sub-clover pastures. Lucerne is only grown on the landformed areas because of waterlogging problems with lucerne on non-landformed layouts, and sub-clover is produced on both layout types. Sub-clover can also be grown as a dryland enterprise if irrigation water is limiting. Both lucerne and sub-clover are directly consumed by livestock. Sub-clover can also be baled into hay for feeding in later periods.

The values used in the model's objective function are shown in Table 1. Note that only the second-cross lamb and sub-clover activities have positive objective function values, while the remaining activities have negative values as they are production inputs. The objective function is to maximise whole-farm gross margin. Sub-clover dry matter production is calculated from the production function;

$$\text{Daily growth rate} = 1.08t - 0.00897t^2 + 0.00002324t^2$$

where t = time (days). Dry matter production is 10.42 and 9.02 tonnes per hectare for landformed and non-landformed sub-clover respectively. The annual lucerne dry matter production is 14.75 tonnes per hectare. These yield figures are converted to an energy equivalent in livestock months (LSM's) to be consistent with the feed

Table 1: Objective function values of model activities in Example 1

Second-cross lambs ($/ewe)	50.00
Sub-clover hay ($/bale)	2.50
Lucerne ($/ha)	40.00
Landformed sub-clover ($/ha)	30.00
Non-landformed sub-clover ($/ha)	25.00
Dryland sub-clover ($/ha)	10.00
Irrigation water ($/megalitre)	12.73
Hay making ($/bale)	1.35
Permanent labour ($/man year)	30,000

Table 2: Seasonal feed energy and labour coefficients in Example 1

	Spring	Summer	Autumn	Winter
Feed supply (LSM's/ha):				
Lucerne	66.90	91.55	51.47	35.60
Landformed sub-clover	49.98	0.00	32.59	56.23
Non-landformed sub-clover	43.16	0.00	28.14	48.90
Dryland sub-clover	14.38	0.00	8.99	25.48
Feed demand (LSM/ewe):	5.69	4.29	6.67	8.49
Labour requirements:				
Lucerne (hrs/ha)	1.60	4.80	1.91	0.65
Landformed sub-clover (hrs/ha)	1.00	1.19	1.16	0.10
Non-landformed sub-clover (hrs/ha)	0.50	0.76	1.87	0.13
Dryland sub-clover (hrs/ha)	0.10	0.15	0.37	0.03
Second-cross lambs (hrs/ewe)	0.15	0.05	0.07	0.06

Table 3: Monthly irrigation requirements in Example 1 (ML/ha)

	Lucerne	Landformed sub-clover	Non-landformed sub-clover
September	1.12	1.00	
October	0.80		
November	1.12		
December	1.12		
January	1.12		
February	1.16	2.30	
March	0.80	1.40	2.30
April	0.80	0.90	0.70

Table 4: Effect of Paterson's Curse in sub-clover on farm plan

	Without weed	With weed
Farm gross margin ($)	62,175	54,872
Number of ewes	1,669	1,525
Sell sub-clover hay (bales)	5,431	4,958
Lucerne (ha)	78.2	71.5
Landfomed sub-clover (ha)	96.8	103.5
Non-landformed sub-clover (ha)	75.0	75.0
Sub-clover LSM's:		
- spring	4,266	3,897
- summer	0	0
- autumn	6,581	6,012
- winter	11,386	10,405
Lucerne LSM's:		
- spring	5,233	4,782
- summer	7,161	6,544
- autumn	4,026	3,679
- winter	2,785	2,545
Hay making (bales)	6,122	5,592
Feed hay in autumn (bales)	692	634
Allocation (ML's)	1,396	1,379
Operators labour (hrs):		
- spring	505	480
- summer	624	593
- autumn	524	508
- winter	180	167

Table 5: Parameter estimates for economic surplus model		
	Short wool breeding ewe inventory increase	
Parameter	1 %	2 %
Farm lamb price (P_{0F})	20.33	19.85
Lamb production (Q_{0F})	262.59	265.12
Retail lamb price (P_{0R})	87.57	87.10
Retail lamb demand (Q_{0R})	230.79	232.83
Supply shift (K)	-0.14762[b]	-0.14762

[a] given as average 1990 values; prices are in real terms (deflated by the CPI);
[b] K = 19/128.71 where the denominator is the nominal 1990 average farm lamb price.

Table 6: Results of economic surplus analysis - annual benefits from Paterson's Curse control in the MIA ($millions)		
	Short wool breeding ewe inventory increase	
	1 %	2 %
Change in consumers' surplus	1.091	2.172
Change in producers' surplus	7.348	6.620
Change in total surplus	8.440	8.791

energy demands of livestock. The detailed seasonal demands and supply of feed energy, along with seasonal labour demands, are given in Table 2. Lucerne requires 10 megalitres per hectare of irrigation water, sub-clover on landformed layouts 5.6 and sub-clover on non-landformed layouts 4.9 megalitres per hectare. The monthly irrigation requirements specified for these activities in the model are given in Table 3.

The differences in the with and without weed situations are indicated in Table 4. The results demonstrate that the impact of Paterson's Curse, represented through a 20 percent decline in sub-clover pasture dry matter production, reduces farm gross margin by $7,303, or 12 percent. Breeding ewe numbers decline by 144 ewes (8.6 percent) because of the lower feed availability. Furthermore, sales of sub-clover hay decline by 473 bales (8.7 percent). There is a small increase in the area of landformed sub-clover, 6.7 hectare, at the expense of lucerne pasture. This occurs because winter feed availability becomes a limiting resource as ewe feed requirements are highest in this period (Table 4). As lucerne provides only minimal feed in winter (Table 4 and Table 6), it is offset to some extent by the higher winter producing sub-clover despite the fact that this activity has suffered a yield decline due to an infestation by Paterson's Curse. Overall, the effects of Paterson's Curse is to reduce whole farm profit by approximately $29 per hectare. At present gross margin estimates, this loss is equivalent to about 1.5 breeding ewes per hectare.

Industry model analysis The significance of this loss to the prime lamb industry was evaluated using the methods detailed in Section 4. Here, the main effect of Paterson's Curse control was expressed through the increased number of breeding ewes that could be carried in the region on the additional feed, and the subsequent effects of this on the Australian lamb industry. As a simplification, the breeding ewe change was assumed to increase the short wool breeding ewe inventory by one percent. The other data required were the extent of the lamb supply change following weed control, and the resulting changes in the equilibrium prices and quantities. The supply shift parameter (K in equation 4.2) was derived from the LP solution and was estimated to be a 19 cent per kilo reduction in the cost of lamb production. The lamb prices and quantity changes (Table 5) were derived from an econometric simulation of what were the before and after weed control situations as were represented by the short wool breeding ewe inventory increase. A two percent inventory increase was also evaluated for comparison.

Economic surplus analysis Incorporating these parameters in the economic surplus equations 4.4 and 4.5 yielded the benefit estimates for Paterson's Curse control (Table 6). The results indicate that the control of this weed in one New South Wales lamb producing region has the potential to generate significant annual benefits to Australian lamb producers and consumers. Producers gain because the revenue gains from the increased lamb production outweighs the losses from the slightly reduced farm lamb price. Lamb consumers gain from the combined effects of higher quantities of lamb on the market and the corresponding lower retail prices. Producers gain the greatest benefit share because lamb has a low price elasticity of supply and an elastic retail demand relative to other meats in the Australian domestic meat market. Overall, the lamb industry has the potential to gain about $8.5 million per annum where improved weed control in a small part of the industry enables higher lamb production in the lamb industry. This is despite the falls in both farm and retail prices as a consequence of the production increases[5].

It should be noted that these benefits are net of the input costs of lamb production and weed control which are incorporated in the industry supply curve, but they do not include the costs of the development of any new Paterson's Curse control technology that may be developed. Also, the partial nature of the analysis (see footnote 5) means that there will be elements of both over- and understatement of the benefits. The benefits will be partly overstated because they do not consider the adjustments in closely related product markets, such as the effects on the demand for other meats from increased lamb supplies and lower retail lamb prices. Also, the benefits may be understated since other industries (e.g., wool and fodder) are also likely to benefit from improved weed control (a benefit-cost analysis has not been attempted because the costs of research into this weed have yet to be determined).

6.2 Example 2

Background In this example, a simulation model is used to examine the economic impact of a range of management strategies for the control of wild oats as a major weed of Australian cropping systems. Medd *et al*. (1995) demonstrated that wild oats can be substantially reduced in the wheat phase of a rotation by the integrated use of seed kill tactics involving the late application of the herbicide flamprop-methyl. This option targets wild oat seed production and does not substitute for the need to undertake yield conservation measures of pre- or early post-emergence application of herbicides.

Methodology A Monte-Carlo simulation model was developed to track the size of the seed bank over a 10 year period and assess the economic benefits of seven alternative control strategies.

a) No annual control.
b) Plant kill control only annually.
c) Seed kill control only annually.
d) Plant and seed kill control annually.
e) Summer crop rotation with no annual weed control during the wheat phase.
f) Summer crop rotation with annual plant kill control during the wheat phase.
g) Annual decision to determine whether to use no control, plant kill only, seed kill only or plant and seed kill combined.

For options (a) to (d) and (g), the farming system is based on a continuous wheat crop. For options (e) and (f) the rotation used is three years of wheat followed by a winter fallow, sorghum crop, winter fallow and another three years of wheat. For the annual decision option (g) the optimal annual strategy is determined by comparing the marginal benefits from plant kill, seed kill and combined plant and seed kill in the following year. The option which gives the highest marginal benefit in year $t+1$ is implemented in year t. If the options give negative returns in year $t+1$, i.e., the marginal cost exceeds marginal revenue, then no control option is implemented in year t.

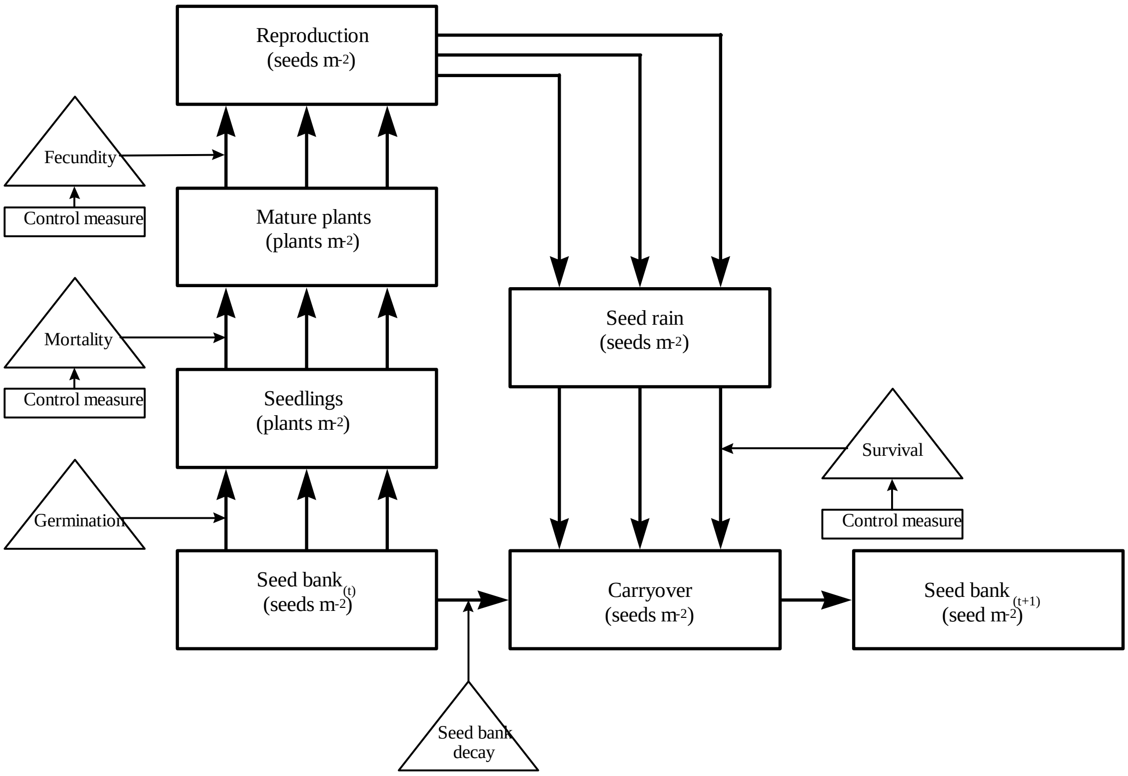
The critical state variable which measures the impact of control on population size is the seed bank. Figure 4 depicts the annual dynamics of wild oats which reproduces only by seed. In a single generation, some seeds germinate giving rise to seedlings, some of which survive and mature, reproduce, die and deposit seed to the seed bank. To capture the asynchronous germination behaviour of wild oats in a season, three cohorts (illustrated by the arrow streams) are simulated.

It is assumed that the initial seed bank size is 500 seeds per square metre for all options. It is expected that in any season 50 percent of the seed bank will germinate in the proportion of 30 percent cohort 1, 60 percent cohort 2 and 10 percent cohort 3. The residual seed remains dormant, but decays or loses viability such that 25 percent is carried over and is available for germination in the following year.

The survival rate of plants and the seed rain survival are uncertain and have been modelled as stochastic variables (Table 7). Plant survival is assumed to vary for the different management options while seed rain survival is constant for the three cohorts. The fecundity equations used for estimating

[5] Because this example considers a technology which affects only part of the lamb industry in a specific region, the more complete evaluation of the benefits from weed control should also consider how the regional lamb supply shift relates to the lamb industry, as this might influence the overall level of industry benefits. Edwards and Freebairn (1982) have described the economic rationale for this level of benefit disaggregation and the methods required to estimate them.

Figure 4: *Seed bank dynamics*



reproduction by the wild oat population are those estimated by Medd *et al.* (1995). Under the no control and plant kill options seed production (y) (seeds per square metre) for each cohort is estimated as follows, where x is wild oat plant density (plants per square metre):

cohort 1: $\ln y = 8.6 \ln x(0.74 + 0.88 \ln x)^{-1}$
cohort 2: $\ln y = 7.6 \ln x(1.2 + 0.8 \ln x)^{-1}$
cohort 3: $\ln y = 6.8 \ln x(2.0 + 0.67 \ln x)^{-1}$

When a seed kill strategy is adopted seed production for all cohorts is given by the equation:

$$\ln y = 7.42 \ln x(2.04 + 0.66 \ln x)^{-1}$$

The proportion of seed produced which enters the seed bank (seed rain) also depends on the management option (Table 7). Wheat yield loss from wild oats is a function of the density of mature wild oat plants. The following yield loss due to competition used by Medd and Pandey (1990) has been adopted in this analysis:

$$\text{Loss} = YW/(a+bW)$$

where Y is the weed-free yield (Table 8), W is the density of wild oats (plants per square metre) and a = 104.4 and b = 1.22 (from Martin *et al.,* 1988).

The herbicide rates for the plant kill and seed kill strategies are as follows:

Plant kill:	Triallate @ 2 L per hectare
Seed kill:	Flamprop-methyl @ 2.25 L per hectare plus Uptake of 0.5% v/v.

The cost of the herbicide treatments, active ingredients plus application costs, is given in Table 8. Wheat and sorghum prices were calculated as five year averages over the period 1990-91 to 1994-95. Yields and variable costs for wheat and sorghum were derived from local gross margin budgets issued by NSW Agriculture.

Results For each control option 300 iterations of the simulation model were run to determine the distributions for the seed bank and the NPV's. Without annual control of wild oats the seed bank increased from 500 seeds per square metre to a mean value of around 4,000 seeds per square metre by year 10 (Figure 5a). If the plant kill only option involving the annual application of triallate is adopted, the seed bank still increased to approximately 2,500 seeds per square metre by year 10. This demonstrates the ineffectiveness of relying solely on plant control measures. Alternatively, both the seed kill and

Table 7: Plant and seed rain survival rates for cohorts and alternative strategies (%)

		Plant survival			Seed rain survival		
Option		Cohort 1	Cohort 2	Cohort 3	Cohort 1	Cohort 2	Cohort 3
No control	a	0	70	25	30	30	30
	b	15	85	20	60	60	60
	c	30	95		75	75	75
Plant kill	a	0	10	25	30	30	30
	b	15	25	20	50	50	50
	c	30	50		60	60	60
Seed kill	a	0	50	50	5	5	5
	b	15	85	10	20	20	20
	c	30	95		40	40	40
Plant and seed kill	a	0	5	25	5	5	5
	b	15	25	20	20	20	20
	c	30	40		30	30	30
Summer crop	a	0	0	0	0	0	0
	b	15	5	10	0	0	0
	c	30	10		0	0	0

where:
a = minimum value of a triangular distribution for cohorts 1 and 2 for plant survival and seed rain survival, and mean of a normal distribution for cohort 3 for plant survival; b = likely value of a triangular distribution for cohorts 1 and 2 for plant survival and seed rain survival, and standard deviation of a normal distribution for cohort 3 for plant survival; c = maximum value of a triangular distribution for cohorts 1 and 2 for plant survival and seed rain survival.

combined plant and seed kill options resulted in rapid seed declines in the seed bank to negligible seed numbers by year 10 (Figure 5b) Medd *et al*. (1995). The combined plant and seed kill had the largest impact upon the seed bank, followed by the annual decision rule and then the seed kill option. Rotation options resulted in substantial temporary declines in populations when sorghum was grown, but was not as effective in controlling wild oat seed bank populations overall as options involving seed kill.

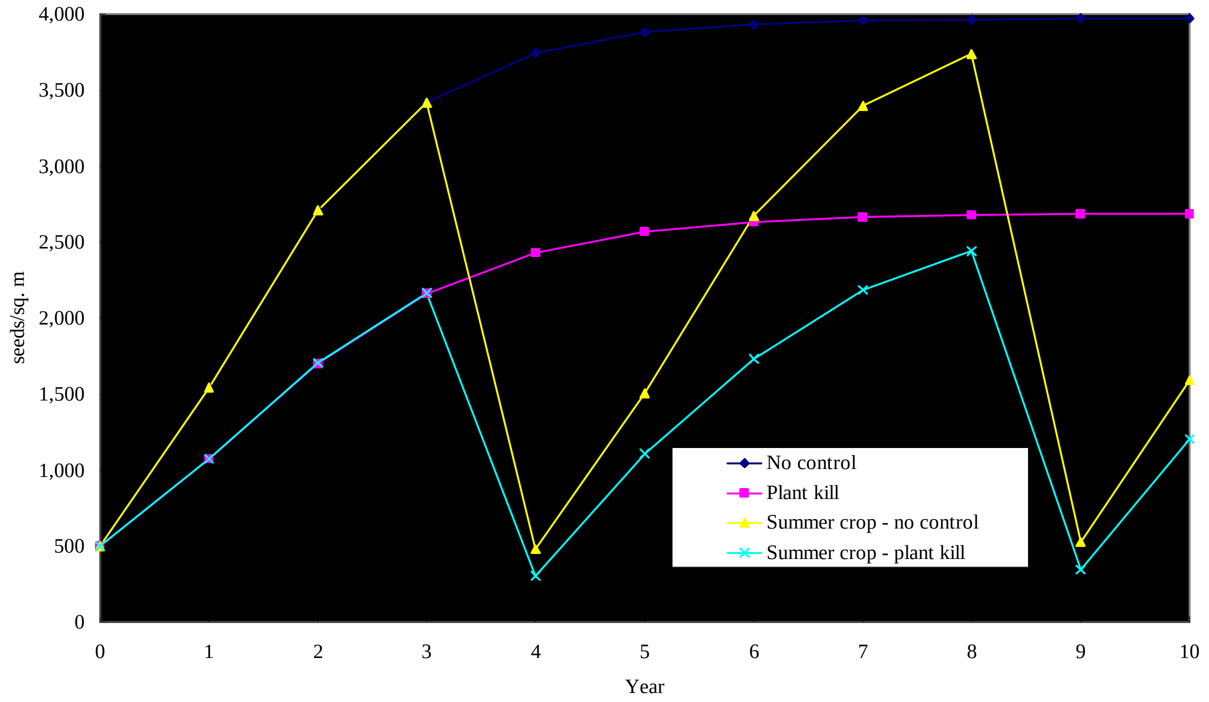
The economic analyses provided NPV’s (annual gross margins discounted to reflect returns, in $ per hectare, in present day dollar values) for each control option. The mean and standard deviations of the NPV’s are presented in Figure 6. Assuming decision makers are risk neutral (i.e., they accept the option with the highest expected return regardless of variance) the annual decision rule is the preferred option for controlling wild oats as it returns the highest mean NPV of $900 per hectare. The combined plant and seed kill and seed kill only options also performed well returning mean NPV’s of $768 and $657 per hectare respectively (Figure 3). The summer crop rotation options gave intermediate returns while the no control and plant kill only options returned negative mean NPV’s.

Table 8: Data used in economic analysis

Wheat price ($/ t)	133
Sorghum price ($/ t)	139
Wheat yield (t/ha)	2.25
Sorghum yield (t/ha)	3.75
Wheat variable cost ($/ha)	118.38
Sorghum variable cost ($/ha)	154.04
Herbicide cost - plant kill ($/ha)	25.4
Herbicide cost - seed kill ($/ha)	19.31

If decision makers are risk averse then consideration needs to be given to the variability in returns as well as the mean values. The procedure of stochastic dominance can be used to identify and rank risk efficient strategies when risk preferences are unknown (Anderson, 1974; Anderson *et al*., 1977). The various classes of stochastic dominance are first-degree, second-degree and stochastic dominance with respect to a function (Meyer, 1977a,b). The estimated cumulative probability distribution functions for the control options are presented in Figure 7. An option exhibits first-degree stochastic dominance if it lies completely to the right of another

Figure 5: *Seed bank dynamics for management options (a) without seed kill and (b) with seed kill options*



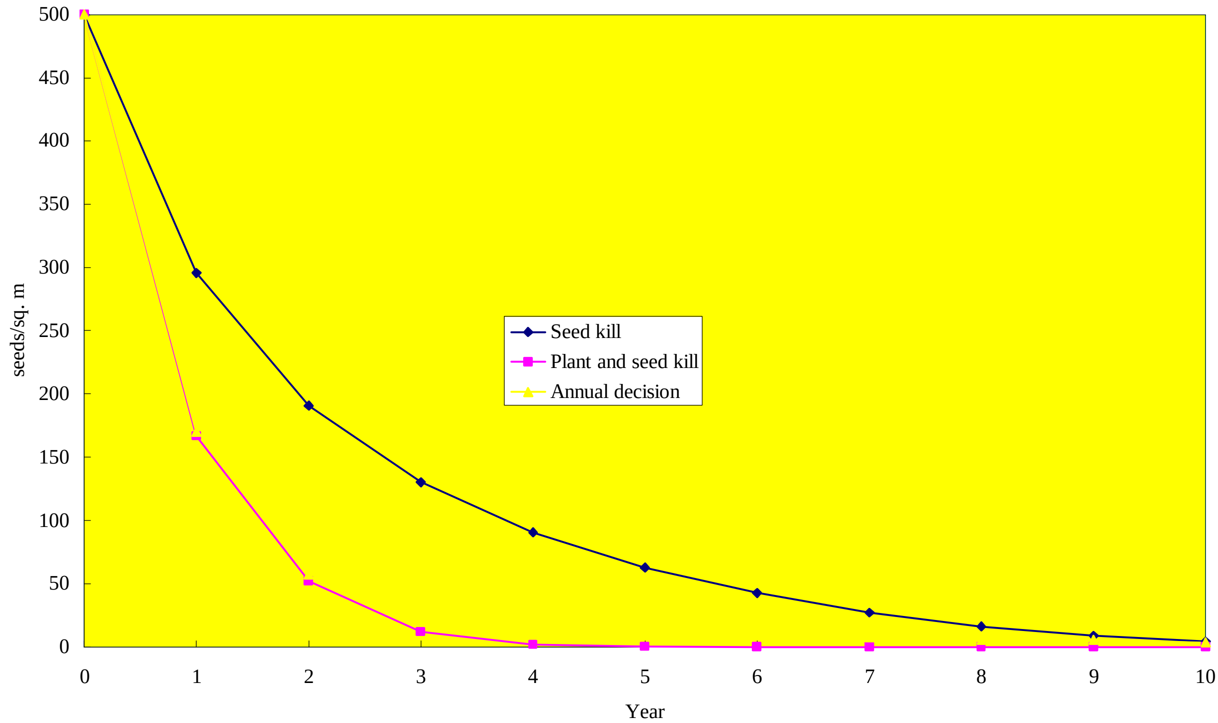


Figure 6: *Net present value for the alternative control options ($ per hectare)*

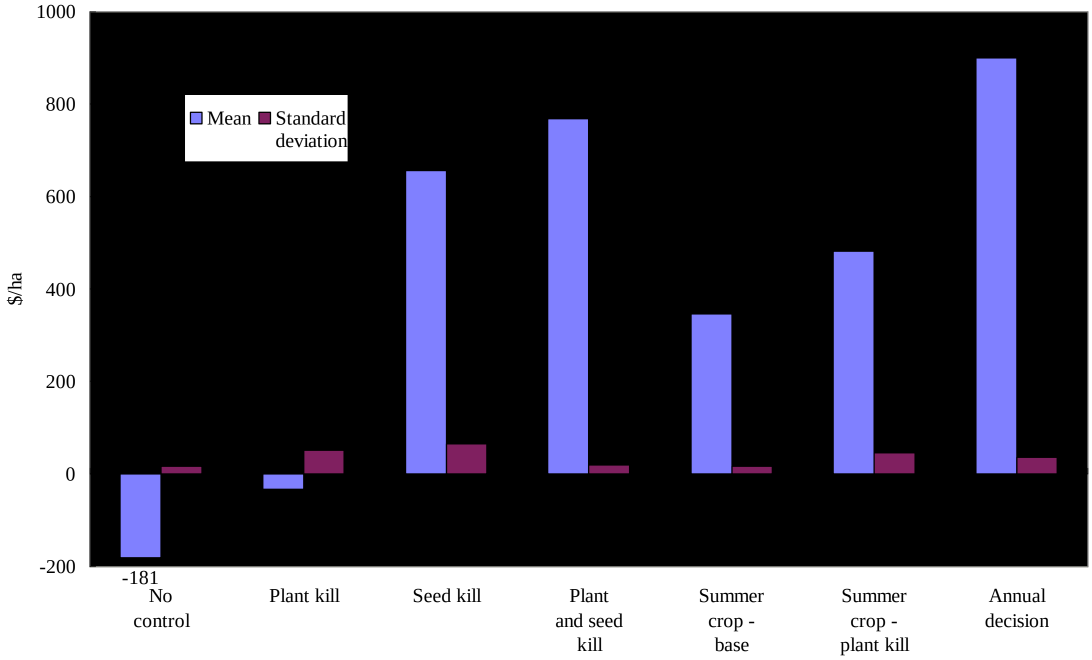
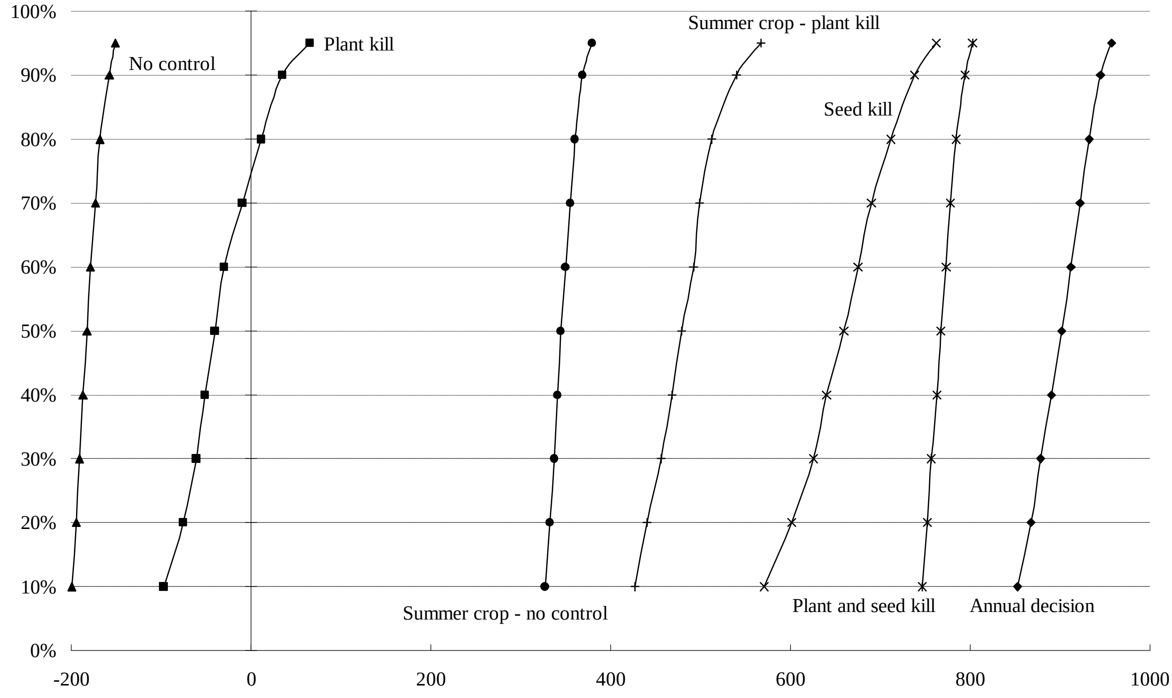


Figure 7: *Cumulative distribution functions for control options (seeds per square metre)*



for all percentile values. On this basis the annual control option is preferred followed by the plant and seed kill option. Given the degree of dominance of the annual decision rule option over the others it would appear that this result is robust under a wide range of data and probability distribution assumptions.

The results of this example indicate that economic benefits can be maximised by minimising seed bank populations. However, the preferred option did not result in the minimum seed bank population. This demonstrates the need to consider the marginal costs of weed control along with the marginal benefits from reducing wild oat seed populations. It is therefore apparent that decision rules which involve a fixed threshold will be sub-optimal.

6.3 A qualification

The intention of the above examples has been to demonstrate the application of an integrated economic system for evaluating weed problems in agricultural production. These methods are required because the nature of the supply and demand relationships in most of Australia's rural markets requires the consideration of the effects on both producers and the broader industry in evaluating the impacts of weeds and the likely benefits of their control. They are suited to those situations in which weeds restrict production and where weed control leads to supply increases. It is likely that much more modelling rigour will be necessary in evaluating the weed management problems which will be defined during the course of the CRCWMS program.

7. Summary

The objective of this paper has been to describe the use of an integrated economic system for evaluating the impacts of weeds and the benefits of weed control in Australian rural industries. This objective recognises that improved technology adoption is an important source of productivity gains in farm production and that improved weed control is a prominent example of a technology which could produce such gains.

Producers benefit from the adoption and maintenance of improved weed control through opportunities to lower their production costs. However, widespread weed control can be expected to have market impacts where it results in increased output. Because weed control is likely to have economic implications beyond the farm, an economic modelling approach which considers both the farm and market components of the affected industry is required to assess the potential benefits.

Production systems models establish the output and revenue changes resulting from weed control under farm constraints and producer objectives. A number of possible modelling methods were described in Section 3. The approach adopted for any particular evaluation will depend on the characteristics of the farm, the nature of the weed problem and the technology being modelled. The results of applying these models provide producers with assessments of the benefits of adopting the weed management options. By highlighting the productivity and profitability changes, producers gain an appreciation of those weed control options best suited to their situations and improving resource use is encouraged as a result. An important part of this analysis is the indication of the sensitivities of the results to changes in the levels of the major parameters. Significant changes in these results may then provide guidelines to weeds research.

Industry supply responses are estimated by aggregating the farm responses under an assumed level of technology adoption across the industry. With estimates of the supply and demand curves, the type of supply shift, and the relationship between producer and consumer prices, measures of total benefits and costs from improved weed control are derived. Again, several methods were described in Section 4, and the choice among them depends on the characteristics of the problem. Both sets of results are useful in identifying the options in weed research programs to allow the efficient allocation of the research budget.

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Appendix

The specification of the Australian lamb industry model and the results of its dynamic validation process are given in Tables 9 and 10. These are further detailed in Vere, Griffith and Bootle (1993, 1994). A simplified diagram of this model's components and linkages is presented in Figure 8. The model was estimated from quarterly data over the period 1969:1 to 1992:4. The important components of the validation process are the simulation R^2's which indicate the model's ability to explain variation in each of the series in the context of a dynamic system, and the coefficients of actual on predicted which establish the correlation between the actual data and the corresponding series generated by the model.

***Figure 8**: Components and linkages in the Australian lamb industry model*

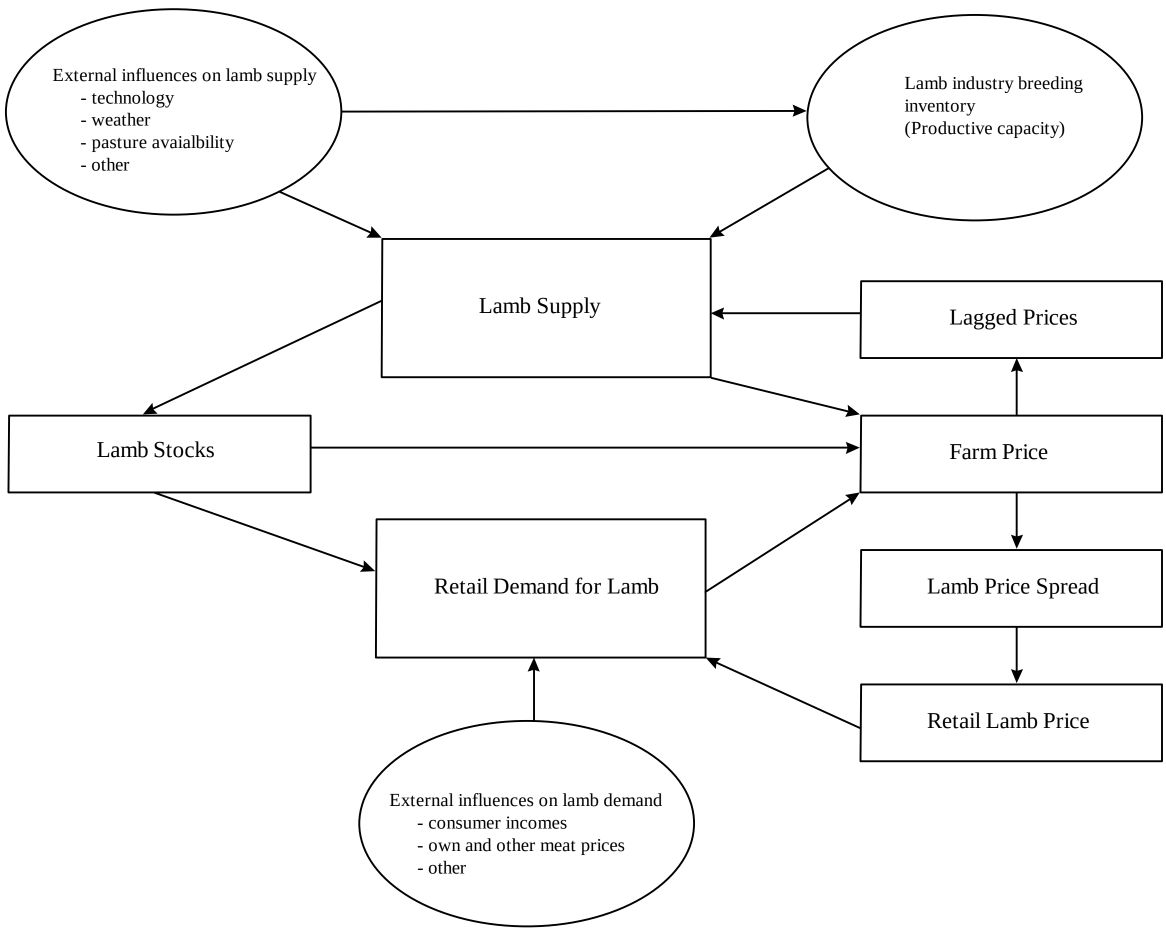

Table 9: Structural econometric model of the Australian lamb industry: specification details

Block	Dependent Variable		Explanatory Variables
Inventory	Short wool matings	f	Lagged short wool inventory (INSWAU), lagged farm price ratios, improved pasture area, drought dummy variable
	Long wool matings	f	Lagged long wool inventory (INLWAU), lagged farm price ratios, improved pasture area, drought dummy variable
ratios, variable	Corriedale-Polwarth	f	Lagged Corriedale-Polwarth inventory (INCPAU), lagged matings farm price improved pasture area, drought dummy
	Adjusted composite breeding inventory	=	δ^{SW} INSWAU + δ^{LW} INLWAU + δ^{CP} INCPAU + $(1-\delta^{LW})$ $INLWAU_L$ + $(1-\delta^{CP})$ $INCPAU_L$
Production	Lamb production	=	Slaughterings * average slaughter weight
	Lamb slaughterings	f	Adj. breeding inventory, lagged slaughterings, improved pasture area, lagged wool price
Demand	Lamb consumption	f	Income, retail prices of lamb, beef, pork and chicken
	Total lamb demand	=	Per capita consumption * population
	Net lamb exports	f	Production, lagged export price, closing lamb stocks
Price	Saleyard lamb price	=	Market balance = production + closing stocks - total demand - exports - opening stocks
	Retail lamb price	=	Saleyard price + marketing margin
	Industry revenue	=	Production * saleyard price

Notes: constant terms, seasonal dummy variables and time trends omitted.

Table 10: Structural econometric model of the Australian lamb industry - e *x post* dynamic validation; 1969:1 to 1990:4

Block	Endogenous variable	Correlation coefficient squared	Root mean squared error (% of mean)	Theil statistic	% error due to bias	% error due to B ≠ 1	Coefficient (B) of actual on predicted
Inventory	Short wools	0.98	11.1	0.05	0.03	0.07	1.03
Inventory	Long wools	0.90	19.0	0.07	0.26	0.04	1.02
Inventory	Corr.-Polw' th	0.97	21.1	0.07	0.09	0.18	0.92
Inventory	Adj. Invent. 1	0.77	5.0	0.05	0.14	0.01	0.94
Inventory	Adj. Invent. 2	0.98	7.1	0.07	0.05	0.01	1.01
Production	Slaughterings	0.72	8.0	0.08	0.05	0.00	0.99
Production	Production	0.70	8.0	0.08	0.05	0.00	1.03
Demand	Consumption	0.79	8.1	0.08	0.03	0.01	1.06
Demand	Demand	0.65	8.0	0.08	0.04	0.03	1.15
Demand	Net exports	0.49	26.0	0.25	0.02	0.08	0.76
Price	Saleyard price	0.72	17.1	0.17	0.03	0.08	0.84
Price	Retail price	0.78	6.0	0.06	0.03	0.00	0.97
Price	Total industry revenue	0.81	13.0	0.13	0.03	0.15	0.83

Notes: [a] This is Theil' s 1961 inequality coefficient.