The importance of seasonal variability on measuring the benefits of a technology: A case study of integrated weed management

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Abstract

Agricultural research is a risky activity, with uncertainty in the research process as well as the physical and economic environment. The impact of seasonal conditions upon the performance of a technology is an important source of uncertainty. One of the unrecognised benefits of an integrated weed management system is the potential for producers to tactically respond to the influences of seasons upon weed management. This paper presents a stochastic and dynamic modelling system for assessing the long-term benefits of alternative weed management strategies. A case study of an evaluation of alternative IWM strategies involving herbicide and non-herbicide options is presented. The study compares the result of applying deterministic and stochastic frameworks to the problem using a stochastic dynamic programming model. It is concluded that for research evaluation of technologies that involve complex biological systems, ignoring the impacts of seasonal variability, responses to risk and temporal dynamics can lead to incorrect conclusions. Depending upon the issue at hand, the costs of this may be high.

Key words: weeds, bioeconomic modelling, stochastic dynamic programming, uncertainty.

1. Introduction

Agricultural research is a risky activity, with uncertainty in the research process as well as the physical and economic environment (Anderson 1991). Uncertainties in the research process involve: the time taken to complete the research is unknown; the scientific outcome is unknown; the impact of new knowledge on yields and costs are unknown when the research has begun; and the time lags in the adoption are uncertain (Alston *et al*. 1995).

There may be important interactions between weather and technologies, thus research may impact upon the riskiness of agricultural production. The impact of seasonal conditions upon the performance of a technology and the potential strategic and tactical responses by farmers to the uncertain outcomes may be important in valuing the research benefits of a technology (Anderson 1991). Consequently, the measure of the expected benefits has a distribution around it, which is a function of the probability distributions of uncertain input variables.

The objective of this paper is to determine the effect of seasonal variability and the role of tactical decision making upon estimation of the benefits of an agricultural technology. The case study is the economic benefits from various integrated weed management (IWM) options for wild oats (*Avena* spp.) in the southern NSW cropping region.

Differences in optimal weed management decision rules are derived from deterministic and stochastic simulations of a dynamic programming model. The economic impact of the

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different decision rules is then derived for both the deterministic and stochastic conditions using a stochastic simulation model. The results from this analysis indicate the relative importance of seasonal variability and tactical decision making in estimating the benefits of IWM. These results can help decide whether the additional expense of stochastic modelling is justified.

2. Weeds, risk, uncertainty and decision-making

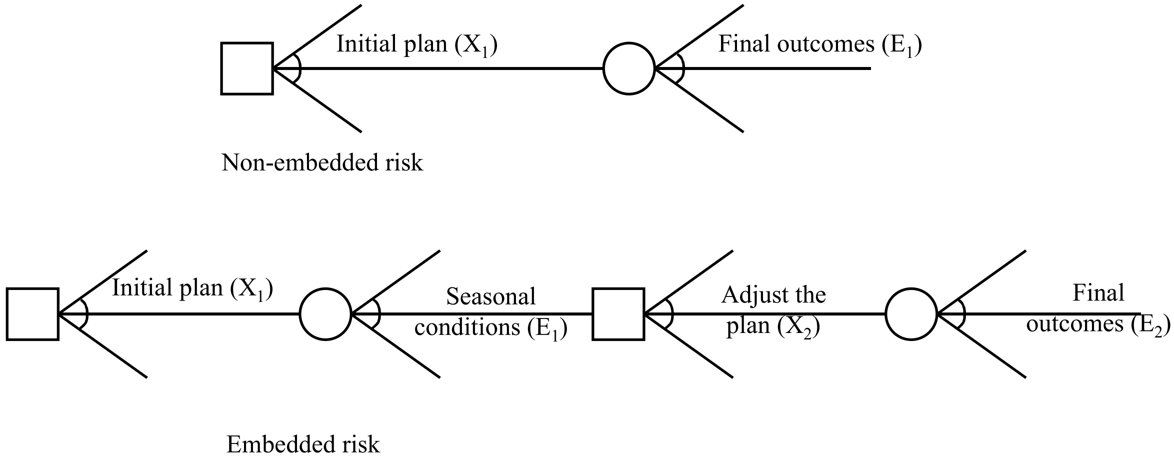
Much of the previous research of risk and uncertainty in weeds has concentrated on the role of risk in herbicide efficacy and the impact of risk aversion by farmers (Auld and Tisdell 1987; Carlson 1984; Deen *et al*. 1993; Feder 1979; Horowitz and Lichtenberg 1994; Olson and Eidman 1992; Pannell 1990, 1991, 1995). This paper does not consider the issue of the impact of farmers risk attitudes upon decision-making, or whether pesticides/herbicides are risk reducing inputs or not. Following the advice of Pannell *et al*. (2000) and Hardaker (2000) we consider the topic of risk aversion to be a minor component of the overall weed problem. In this paper, emphasis is placed on properly accounting for the effect of seasonal conditions upon certain biological relationships and accounting for the potential responses of farmers to uncertain outcomes.

Seasonal conditions are the major source of risk faced by farmers in the Australian cropping systems. Both risk averse and risk-neutral farmers can make a variety of tactical adjustments to their farming strategies in response to short-term seasonal conditions so as to lessen the economic consequences of such risks. Ignoring the role of tactical adjustments can have serious consequences in terms of underestimating the economic performance of some strategies.

Various authors have suggested that accounting for risk aversion may be of less importance than ensuring that the appropriate responses by decision-makers to risk is properly incorporated into the decision problem (Hardaker 2000; Kingwell 1994; Kingwell *et al.* 1993; Pannell *et al*. 2000). To account for the impact of the appropriate responses requires a better understanding of the nature of the risk and the possible strategic and tactical responses that decision-makers have to that risk.

Hardaker *et al*. (1991) provide a useful distinction between the types of risk faced by decision-makers. Using the outline decision trees in Figure 1, risk can be either non-embedded or embedded. In this figure the convention is followed of representing decisions (X_i) with multiple options by decision fans, shown with squares for their nodes, and uncertain events (E_i) with many possible outcomes by event fans represented with circles as their nodes. At each node the tree is continued for only one of the many possible branches.

The concept of non-embedded risk is based on the assumption that it is realistic to model the system as if all decisions are made initially, at X_1 in Figure 1, and that uncertainty unfolds subsequently in terms of risky consequences of the choice taken ie. E_1. 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.

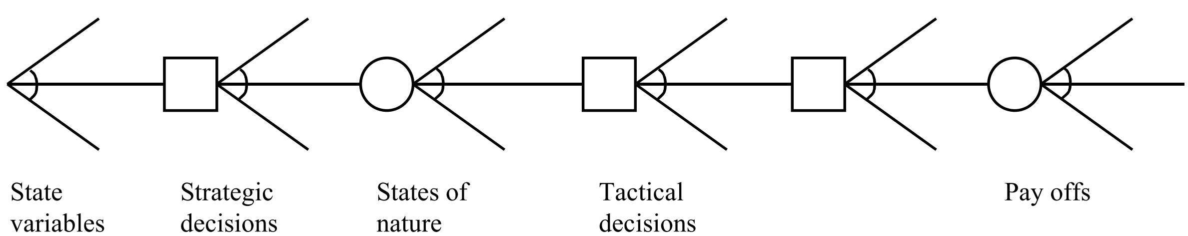


Source: Hardaker, Pandey and Patten (1991)

Figure 1 Outline decision trees for non-embedded and embedded risk

Most farm decision problems involve embedded risk, but many of the mathematical programming approaches that incorporate uncertainty do not account for embedded risk. Generally, non-embedded risk is confined to objective function coefficients while in embedded risk both the objective function and production 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 classified as stochastic programming models.

Sequential decision making by farmers is a feature of problems of embedded risk. A characteristic of this process is the ability of individuals to tactically respond, not only to the intervening states of nature, but also with the initial strategic decisions made. This concept is illustrated in Figure 2, again using the concept of an outline decision tree. In this figure the same convention is followed as in Figure 1.



Source: Trebeck and Hardaker (1972)

Figure 2 Sequential decision making

The initial state variables describe the situation of the farm or field at the time of considering the decision problem, such as size of the weed seed bank. The decision-maker has to make strategic decisions (such as the crop type and whether or not to apply a post-emergent herbicide) with only subjective notions about the future states of nature. Once the outcome of an uncertain event becomes apparent (eg. the effects of weather upon herbicide efficacy), the decision-maker can make tactical decisions (such as applying a late post-emergent herbicide to reduce seed production of surviving weeds). In sequential decision-making, the uncertain pay-offs associated with each strategic decision/state of nature/tactical decision sequence become apparent.

Kingwell (1994) reports that ignoring within season-tactical adjustments can lead to not only an underestimation of the profitability but also to incorrect conclusions about optimal resource use and policy impacts. In a study of wheat supply in Western Australia, Kingwell determined that ignoring the within-season tactical adjustments led to a significant over-estimate of wheat supply response. Such incorrect results have serious implications for policy advice based on these estimates.

3. Methodology

3.1 Model structure

The study involves the use of a stochastic dynamic programming model (SDP) that interacts with a range of biological models of the weed problem (Jones 2003). Dynamic programming has had widespread application in agriculture and natural resources research (Kennedy 1981, 1986, 1988; Taylor 1993). The objective of the model is to determine the economic benefits of IWM for managing weed populations over a 20-year time horizon. The state variable is the weed seed bank, the decision variable is combinations of different weed control technologies, and the case study is weed wild oats (*Avena* spp.).

The economic benefits of IWM are expected to be influenced by both the dynamic aspects of the weed problem and by uncertainty in weed population dynamics, weed control efficacy and crop yield. The SDP model was developed so as to measure the effects of this uncertainty on the weed management problem and thereby evaluate the benefits of IWM. In many decision problems the equation of motion depends not only upon the state of the system and the decision taken, but also on unpredictable events outside the control of the decision-maker. The net return function may likewise depend upon unpredictable events. If random events affecting the net return function and equation of motion at stage t are those occurring at stage t and not any earlier, the problem may be formulated as a SDP problem without additional state variables. Stochastic processes in SDP models are generally described as Markov decision processes or Markov chains.

The stochastic problem is to maximise the expected present value (EPV) of profit (π) from a T-period decision process.

$$\max_{u_t} EPV = \sum_{t=0}^{T} \beta^t \pi(x_t, u_t, e_t) \tag{1}$$

Where t is an index of time (years), e is an error term that determines the probability distribution for π and EPV, u is a set of decision variables, x is a set of state variables and β is the discount factor ($1/(1+r)$ where r is the discount rate). Maximisation of this equation is subject to a set of first-order difference equations for the state variables.

$$x_{t+1} = x_t + g(x_t, u_t, \varepsilon_t) \tag{2}$$

Where ε is a random variable (or set of random variables) and defines the probability distribution for the state variable. The recursive equation for the SDP problem is.

$$V_t(i) = \max_k \left\{ p_{ij(n)}^k \left[\pi(i,k) + \beta V_{t+1}(j) \right] \right\} \tag{3}$$

Where k is an index for the decision variable, $V_t(i)$ is the optimal value function from period t to the end of the planning horizon (T) for the i-th state, $p_{ij(n)}^k$ is the joint transition probabilities for the n-th stage return corresponding with the transition from the i-th to the j-th state and the k-th decision alternative.

The biophysical modelling system used in this study is illustrated in Figure 3. The overall modelling process involves the interaction of water balance, weed population dynamics, crop yield, crop rotation and pasture growth models. The crop rotation and pasture growth models are excluded from the analysis in this paper. The biophysical modelling system is driven by daily weather data for the period 1950 to 2002.

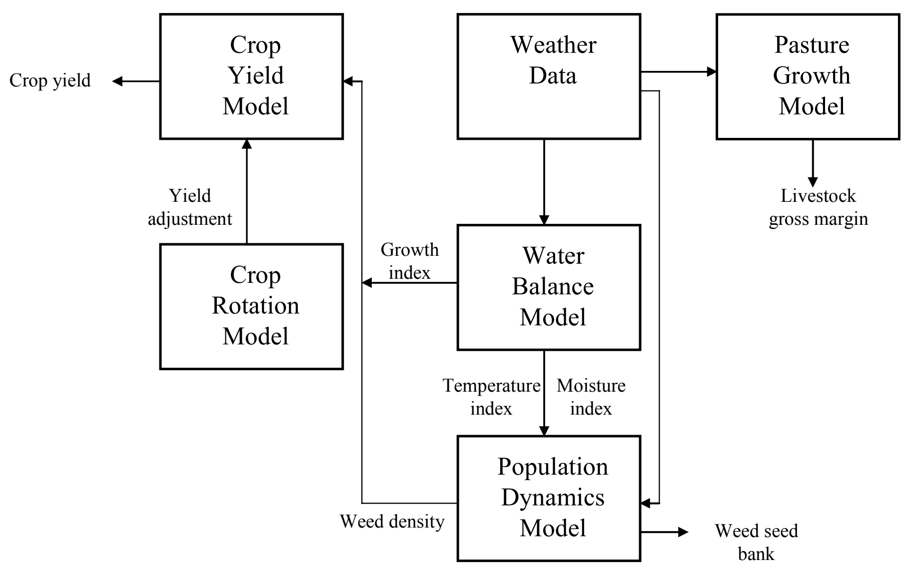


Figure 3 The biophysical model system

The impact of variable seasons upon crop growth and weed population dynamics is derived from the water balance model by calculating daily environmental indexes for soil moisture (*MI*), temperature (*TI*) and light (*LI*) (Fitzpatrick and Nix 1970; Nix 1981). These indexes are then combined to determine a multi-factor growth index (*GI*). The water balance model is necessary to calculate soil moisture levels and consequently the moisture and growth indexes.

The objective of the weed population dynamics model is to calculate the change in the weed seed bank from one year to the next due to a weed management decision. A number of the population dynamics parameters are dependent upon environmental factors such as soil moisture and temperature. Consequently, the outputs of the water balance model are an important input to the population dynamics model.

The crop yield model is comprised of two components; a crop growth sub-model and a yield-loss sub-model. The growth indexes derived from the water balance model are used in the calculation of crop growth and, therefore, weed-free yield. The yield-loss sub-model is based upon a density based yield-loss equation (Cousens 1985) and is linked to the population dynamics model for the determination of weed density.

There are two specific purposes of the population dynamics model. The first is to determine the plant density that results from a given initial weed seed bank and weed management decision. This is required by the crop yield model to estimate yield loss due to weed density. The second is to determine the change in the seed bank arising from a given initial seed bank and management decision. This information is used to track population changes through time and to estimate probability distributions of population change for a given weed management decision. This latter data is required to derive the state transition probabilities for the SDP model.

The population dynamics model is developed for both deterministic and stochastic scenarios. The deterministic case provides a unique change in the seed bank for a given decision and initial seed bank. The stochastic version uses a combination of growth indexes and biological response functions for selected population dynamics parameters to predict probability distributions of the state variable.

The population dynamics of a weed is represented by separate stages in the life-cycle: seed bank, emerged plants, seedlings, mature plants, seed production and seed rain (Figure 4). This approach allows the use of specific parameters for derivation of the system components such as germination, seedling mortality, density-dependent mortality, plant fecundity, seed survival and decay of dormant seeds.

The annual population recruited (ie. seeds that germinate into seedlings) can be divided into a number of individual cohorts (age-specific portions of the population). Each cohort exerts different levels of competition and experiences differences in mortality and fecundity given the divergent seasonal and crop competitiveness conditions throughout a season. The wide arrow streams in Figure 4 indicate the existence of multiple cohorts. Further details of the population dynamics processes are described by Jones (2003).

Various stages of the weed life-cycle are influenced by environmental factors such as soil moisture and temperature. The stages of the life-cycle included as stochastic variables in the model were germination (g), seedling mortality from post-emergence herbicides (k_2), seed production (R), and the mortality of seed rain due to a late post-emergence herbicide (k_3). All other population dynamic parameters were assumed to be certain and are seedling mortality from cultivation (k_1), mortality of seed rain due to non-herbicide management (k_4), natural mortality of new seed production (k_5), natural mortality of seeds in the seed bank (k_6), seed exports such as from harvesting (x), and seed imports such as from sowing (m).

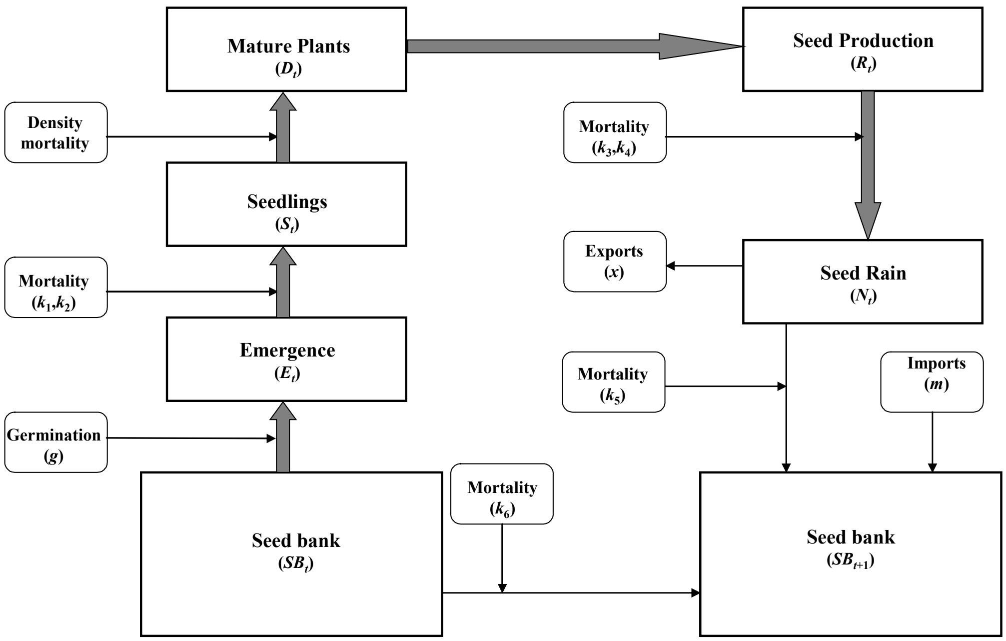


Figure 4 Weed population dynamics

There is a general lack of research and data to quantify the effects of soil moisture and temperature upon many of the life-cycle stages. Exceptions are the estimation of the environmental factors that determine wild radish germination patterns (Young 2001), the efficacy of herbicides on wild oats (Pandey, unpublished; Medd *et al*. 2001) and the efficacy of selective spray-topping on wild oats (Cook *et al*.1999) and wild radish (Madafiglio 2002). Where no published data were present, an expert opinion approach was used to obtain parameters and functional relationships between environmental factors and the population dynamic parameters. Full details of the parameter values are reported in Jones (2003). The following functional forms were used to calculate each of the random variables. The *a* coefficients in the following equations are shape parameters in the respective functions.

Germination

A hyperbolic function was used to represent germination (g) of each cohort (c) as a function of the growth index on specific germination dates for each cohort ($GI_{g\,c}$).

$$g_c = \frac{a_{1c} \times GI_{gc}}{1 + a_{1c} \times \dfrac{GI_{gc}}{a_{2c}}} \qquad (4)$$

Seedling mortality
A logistic function was used to represent the herbicide efficacy (k_2) at seedling stage as a function of the growth index at the date of spraying (GI_s). The herbicide kill is calculated as follows.

$$k_2 = \frac{a_3}{1 + a_4 \times e^{-a_5 \times GI_s}} \tag{5}$$

Seed production
A fecundity equation developed by Medd *et al*. (1995) was used to calculate seed production (R). The seed production was then adjusted up or down according to soil moisture and temperature conditions by multiplying the production value by a seed production adjustment factor (*spaf*). The growth index at flowering stage (GI_f) was used to calculate the *spaf* value.

$$spaf = \frac{a_6 \times GI_f}{1 + a_6 \times \frac{GI_f}{a_7}} \tag{6}$$

Seed rain mortality
Madafiglio (2002) found that the efficacy of selective spray-topping was a function of maximum daily temperature and the growth stage of a weed at the time of spraying. Madafiglio found there was little response in efficacy due to soil moisture. The maximum efficacy occurred at around 24°C and declined to a minimum efficacy at 8°C. A logistic equation was used to derive the efficacy of a selective spray-topping herbicide (k_3) as a function of maximum temperature ($T_{\max}$) on the day of spraying.

$$k_3 = \frac{a_8}{1 + a_9 \times e^{-a_{10} \times T_{\max}}} \tag{7}$$

3.2 Integrated weed management scenarios

A range of possible weed control technologies were selected to represent control at specific stages of the weed life-cycle illustrated in Figure 4; namely the emergence (E), seedlings (S), mature plants (D) and seed rain (N) stages. The weed control technologies chosen were an autumn tickle (which affects seedling emergence), a post-emergence herbicide (which targets seedling survival), increased competition from higher sowing rates (which increases density-dependent mortality and reduces mature plant numbers), and selective spray-topping (which reduces seed rain by killing new seed production).

The following IWM scenarios were constructed to assist in the analysis.
PE – Post-emergence herbicide (H) only available.
PE+AT – Post-emergence herbicide and autumn tickle (AT) available.
PE+IC – Post-emergence herbicide and increased competition (IC) available.
PE+ST – Post-emergence herbicide and selective spray-topping herbicide (ST) available.
ALL – All control options above available.

These scenarios provide a measure of the economic impact of restrictions on IWM. The scenario PE restricts management to a post-emergence herbicide at the registered rate and represents the base from which to value the economic benefits of additional weed control. Scenario PE+AT restricts of weed management to a post-emergence herbicide and an autumn tickle cultivation[§]. Likewise, the scenarios PE+IC and PE+ST involve weed management being limited to a post-emergence herbicide and either increased competition or a selective spray-topping herbicide. The scenario ALL allows access to all the possible weed management options described, and determines the preferred IWM strategy for a given seed bank.

Within season tactical-adjustment is represented by ST as this technology occurs late in the growing season and can be used to minimise seed rain from surviving plants if an earlier weed control (eg PE) has failed due to unfavourable seasonal conditions. The remaining options of PE, AT and IC are strategic decisions as they are decided early in the growing season.

3.3 Economic valuation process

The process used to estimate the economic benefits for each scenario is illustrated in Figure 5. The SDP model was simulated to obtain the optimal deterministic and stochastic decision rules. A Monte Carlo simulation (MCS) model was developed to determine the implications of the stochastic decision rules on NPV and the seed bank timepath as these variables can not be interpreted directly from the SDP results of a stochastic simulation. The MCS model used the same biophysical modelling system, described in Figure 3, used to calculate the transition probabilities and stage returns in the SDP model.

The NPV and seed bank timepath results of the deterministic decision rules were obtained directly from a deterministic simulation of the SDP model. The MCS model was also simulated with both the deterministic and stochastic decision rules, and reported the results for NPV and seed bank timepath in the form of distributions.

This solution process allowed a number of comparisons to be made from the results.

- Deterministic versus stochastic decision rules.
- The deterministic decision rule results (ie NPV and seed bank timepath) derived from the SDP model (D/D).
- The deterministic decision rule results derived from the MCS model (D/S).
- The stochastic decision rule results derived from the MCS model (S/S).

Where D/D is deterministic decision rules and deterministic model, D/S is deterministic decision rules and stochastic (ie. MCS) model, and S/S is stochastic decision rules and stochastic model.

[§] An autumn tickle involves a light cultivation prior to normal tillage operations so as to stimulate weed seed germination, which can then be controlled using tillage or knockdown herbicides prior to sowing.

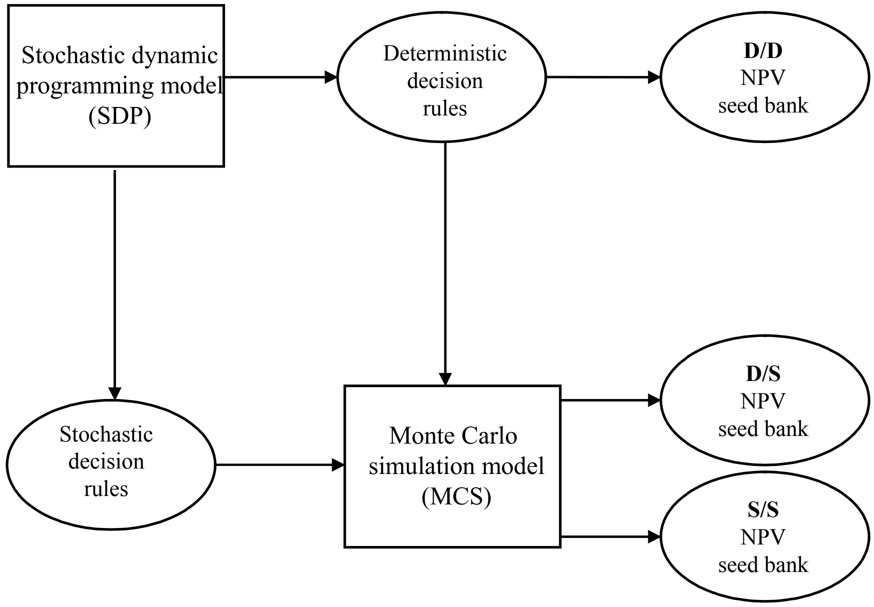


Figure 5 The economic valuation process

4. Results

4.1 Optimal decision rules

The optimal decision rules are given in Table 1 which gives the minimum seed banks where each control option is selected by the deterministic (D) and stochastic (S) models. For each scenario there was no difference in the deterministic and stochastic model decision rules at the higher seed bank levels. The main differences occur at the lower seed banks, with the stochastic model selecting weed control earlier (either 5 or 10 seeds/m^2) than was chosen by the deterministic model (either 20 or 30 seeds/m^2).

The stochastic model also selected the additional weed control options of AT, IC and ST at much lower seed banks than was obtained from the deterministic model. For example, in the case of the PE+ST scenario H was selected at 5 seeds/m^2 (compared to 30 seeds/m^2 for the deterministic model) and ST at 30 seeds/m^2 (compared to 190 seeds/m^2 for the deterministic model).

4.2 Economic benefits of IWM

Three sets of net present value (NPV) results are reported for the case of a 20-year simulation and an initial weed density of 1,000 seeds/m^2. First, the deterministic decision rules and deterministic model simulation (D/D); second, the deterministic decision rules and stochastic model (D/S); and third, the stochastic decision rules and stochastic model (S/S). The NPV results were calculated for each scenario and the means and standard deviations from the MCS model simulations along with the standard deterministic results are reported in Table 2.

Table 1 Optimal decision rules from deterministic and stochastic simulations of the SDP model for five IWM scenarios

	Seed bank control trigger levels (seeds/m^2) Control options							
	H		AT		IC		ST	
Scenario	D	S	D	S	D	S	D	S
PE	20	5						
PE+AT	20	5	320	10				
PE+IC	20	10			130	18		
PE+ST	30	5					190	30
ALL	20	5	300	5	30	30	300	35

D = deterministic model; S = stochastic model; H = post-emergence herbicide; AT = autumn tickle; IC = increased competition; ST = selective spray-topping

Table 2 Net present values from deterministic and stochastic simulations (mean and standard deviation) for five IWM scenarios and an initial weed density of 1,000 seeds/m^2 ($/ha)

	D/D	D/S		S/S	
Scenario		μ	σ	μ	σ
PE	4,792	2,839	516	2,839	516
PE+AT	4,872	2,839	524	2,839	524
PE+IC	5,043	3,818	545	3,818	545
PE+ST	5,017	4,547	589	5,076	599
ALL	5,086	4,692	585	5,115	602

μ = mean; σ = standard deviation

Two key observations are derived from these results. First, the difference between standard deterministic and stochastic analyses can be obtained by comparing the NPV results for D/D against the means for S/S. The NPVs from the stochastic simulations are substantially less for scenarios PE, PE+AT and PE+IC than calculated from the deterministic model. However, the NPV results for scenarios PE+ST and ALL are largely the same. This results in a substantially different value of the economic benefit of IWM when calculated as a percentage difference between the NPV of scenarios PE and ALL. In the deterministic case there is a 6% gain in NPV ($4,792 to $5,086/ha), whereas in the stochastic case the economic gain from adopting IWM was a 78% increase in the mean NPV ($2,839 to $5,115/ha).

The economic impact of differences in the deterministic and stochastic decision rules is obtained by comparing the NPV results of D/S and S/S. This leads to the second important observation: that for the scenarios PE, PE+AT and PE+IC there were no differences in the results, whereas there were substantial differences in the results for PE+ST and ALL between D/S and S/S. The former results were due to the seed bank values for each of these scenarios not declining over the simulation period to a level where there were differences between the deterministic and stochastic decision rules, the latter results are attributable to the selection of weed control, particularly ST, at lower seed banks by the stochastic model. The benefits from IWM were undervalued using D/S, with the gain in NPV between the PE and ALL scenarios being 65% ($2,839 to $4,692).

In this case study the economic benefits of IWM were largely attributable to the ST technology as there was little difference in the mean NPV between scenarios PE+ST and ALL. The stochastic efficiency of the five individual scenarios is illustrated in Figure 5, which shows cumulative distribution functions (CDFs) of NPV. This indicates that scenarios PE+ST and ALL are first-degree stochastic dominant over the remaining scenarios. Although there appears little difference in the CDFs for scenarios PE+ST and ALL, a test for stochastic efficiency using the RiskRoot program (McCarl 1990) determined that the distribution for ALL was marginally dominant.

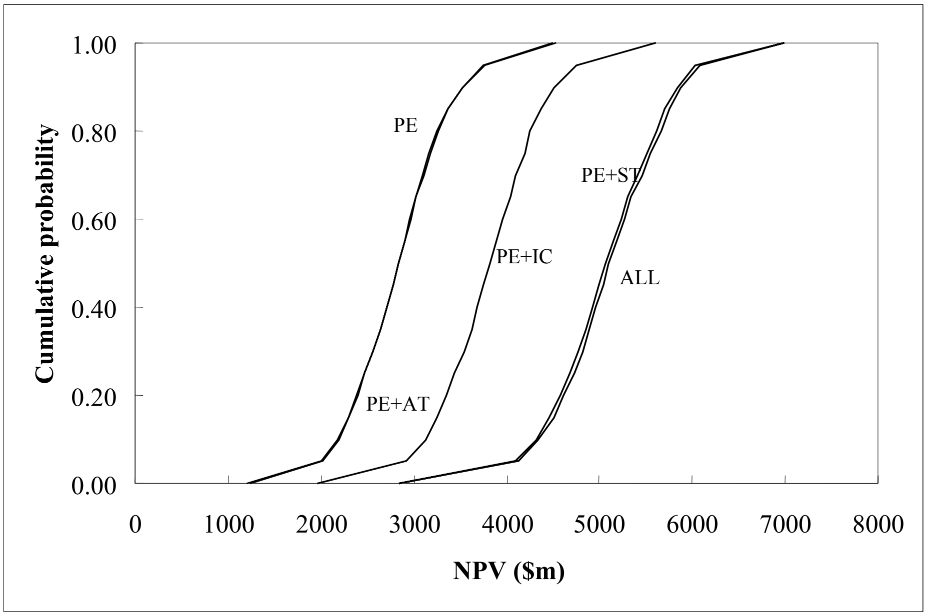


Figure 5 Cumulative distribution functions for the five scenarios using stochastic decision rules and an initial seed bank of 1,000 seeds/m^2

4.3 Changes in the seed bank

Changes in the weed seed bank resulting from a 20-year simulation of the SDP model were derived from both the deterministic and stochastic decision rules, starting with a seed bank of 1,000 seeds/m^2 (Figure 6). Simulations involved applying the decision rules reported in Table 1 in deterministic and stochastic versions of the population dynamics model for each scenario. Reported are the mean and 95th and 5th percentiles from the stochastic model, and the seed bank timepath predicted by the deterministic model. Scenario PE+AT was excluded as the results were identical to the PE scenario.

The deterministic model predicted a decline in the weed seed bank for all scenarios under optimal control. The rate of seed bank decline was increased by the inclusion of the ST technology. The stochastic model yielded a substantially different set of results, with the mean seed banks actually increasing for PE, and experiencing a small decline for PE+IC. The mean seed banks predicted by the stochastic model for scenarios not involving ST (Figures 6a and 6b) were substantially greater than those derived with the deterministic model. The results are dramatically different when ST is available (scenarios PE+ST and ALL in Figures

6c and 6d); the stochastic model resulted in lower seed banks, with the 95th percentiles being below the deterministic model predictions.

These results emphasize the point made in the previous section that the value of IWM only becomes truly obvious with a stochastic model. Comparing the figures for the scenarios PE and ALL shows large differences in the stochastic results, but only marginal differences in the deterministic results.

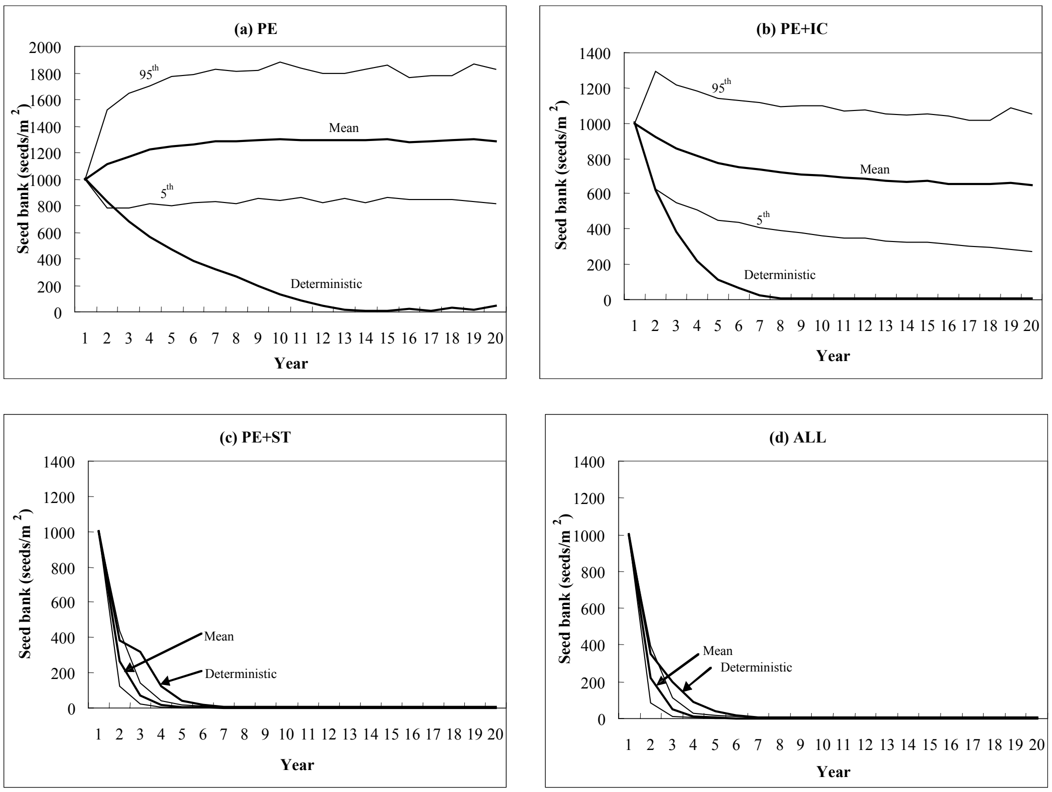


Figure 6 Timepath of weed seed bank (seeds/m^2) for five IWM scenarios from stochastic and deterministic models

4. Summary and conclusions

This paper presents a modelling framework for considering stochastic processes in the valuation of the benefits of integrated weed management (IWM). The models explicitly account for a number of important biological responses to the environmental factors of soil moisture, temperature and light, and these responses have been incorporated into the calculation of state transition probabilities of a stochastic dynamic programming model.

The analysis is based on the solution of deterministic and stochastic dynamic programming (DP) models of a weed population that invades a crop. Both models are based on the same population dynamics parameters, but the stochastic model accounts for year to year variation in seasonal conditions. The DP models are used to derive optimal decision rules based on the size of the seed bank (the state variable). Optimal decisions are defined as those that maximise the net present value (NPV) of the control effort by selecting a package of weed control strategies. The strategies available vary between scenarios and range from herbicide only to a collection of four control options. The decision rules obtained from the DP models were applied to Monte Carlo simulations of the weed-crop system over 20 years.

The analysis shows that there are differences in the optimal decision rules derived from deterministic and stochastic frameworks. However, differences in decision rules are not a sufficient condition to adopt a stochastic analysis; there must be clear differences in the economic consequences of following the different decision rules.

The availability of IWM increased NPV by only 6% compared with a herbicide-only case under the deterministic decision rules. In sharp contrast, the availability of IWM resulted in a 78% gain under the stochastic decision rules. Moreover, when the deterministic decision rules were applied to the Monte Carlo simulation model, there were clear differences in the economic outcome for scenarios involving a selective spray-topping (ST) technology. Consequently, it was concluded that not only was IWM desirable but that technologies such as ST that target seed production and achieve long-term population management are essential features of an IWM strategy.

The results show that reliance upon a deterministic model would have erroneously concluded that there are only marginal gains in the adoption of IWM. The deterministic decision model overestimated the benefits of current post-emergent herbicide strategies because it does not capture the negative economic consequences of large increases in the seed bank in some years of the simulation due to favourable seasonal conditions for weed growth and poor herbicide efficacy.

It is concluded that when performing research evaluation of technologies that involve complex biological systems, the impacts of seasonal variability should not be ignored. The combination of variability and temporal dynamics can lead to incorrect conclusions from a deterministic model. Depending upon the issue at hand, the costs of this estimation error may be high. Therefore the extra effort of developing and solving stochastic decision models is justified, even under assumptions of risk neutrality. These findings support the comment of Pannell (1999) that more sophisticated and detailed analysis may be required to ensure that all the relevant factors that affect the benefit estimation are included.

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