AARES 53rd Annual Conference

2009

Title: Biological control of invasive plant species: stochastic economic analysis

Author and presenter:

Morteza Chalak-Haghighi

Co-Authors:

Arjan Ruijs

Ekko C. van Ierland

Biological control of invasive plant species: stochastic economic analysis

ABSTRACT

We analysed to what extent the stochastic effects of two biological control agents (i.e. weevils and mycoherbicides) affect the optimal choice of Californian thistle control. A stochastic, dynamic optimisation model was set up to analyse strategies that maximise the expected net present values. We analysed the cost-effective strategies to control the thistle for deterministic and stochastic cases. Results show that the stochasticity of the efficacy of weevils does not affect the optimal strategy. Compared to the deterministic case, however, mycoherbicides will be introduced at a higher level of weed density if we take the stochastic effect of mycoherbicides into account.

Key words: Stochastic, Optimisation, Biological control, Californian thistle, Economics.

1. Introduction

Alien invasive species are one of the most significant threats to biodiversity, threatening significant percentages of listed rare and endangered native plant species (Pimental, 2002). Of these, alien weeds are the most costly causing more than a third of the estimated US$350 billion worldwide annual economic damages caused by all introduced pests (Sheppard *et al.,* 2003). Classical biological weed control involves the introduction of exotic natural enemies, such as insects, to reduce the abundance of a plant that has become an invader when spread outside of its native range. The practical aims of biological weed control are to achieve and maintain low population levels and to replace the weed with a more desirable plant (McEvoy and Cox, 1991). Among different ways of controlling invasive plants, biological control is widely regarded as a safer and more suitable alternative to other forms of invasive species management (Pemberton, 2000; Ehler, 1998; McFadyen, 1998; and Thomas and Willis, 1998). Hill and Greathead, (2000) claimed that biological control is a highly cost effective means for controlling invasive weeds on regional scales as compared to chemical control methods. However, biological control agents can have stochastic effects on the target plants because of the difficulties of establishing and adapting to the new environment. Some plants can become resistant against the insect (Derera *et al*., 2000; Ortiz *et al.,* 1995; and Giga *et al.,* 1991). As a result managers do not easily choose for biological control as other controlling measures (such as chemical and mechanical controls) can be more reliable.

The aim of this paper is to analyze if a biological control agent (in our study the insect *Apion Onopordi*) becomes a less attractive option when considering its stochastic effects. For this, we create sets of control strategies some *with* and some *without* the biological control. Then we evaluate which control strategies give the best results if the stochastic effect of the insect is considered. We choose the control strategy that maximizes the expected net benefits obtained from the pasture. For such types of studies a number of dynamic programming models have been set up (see e.g. Odom *et al,*. 2003, Bulte and van Kooten, 1999, Higgins, *et al.,* 1997). When including the stochastic effect of biological controls a stochastic dynamic programming approach is needed. Some studies have been conducted using stochastic dynamic programming (see Bulte E. H. and van Kooten G.C., 1999; and Pandey and Medd, 1991).

Our paper makes new contributions to the previous studies in three aspects. Firstly, we conduct a stochastic optimal control model with a discrete decision variable (consisting of 62 possible strategies) which deals with the stochasticity of introducing a biological agent: weevil, Apion *onopordi,*. In the above mentioned studies either only a single decision variable or a few decision variables were analyzed. Secondly, in this paper we look at two categories of the decision variables. One category is reversible and can be chosen on an *annual* basis. The second category is irreversible and includes the introduction of the insect (weevil). It has the characteristic that once the weevil has been introduced it will remain active in the pasture and therefore does not have to be chosen in the later stages. Thirdly, we focus on the stochastic efficacy of the biological control agent on the invasive plant, while the above mentioned studies mainly focused on the negative effects of biological control and less attention was paid to the success of biological control management of invasive species.

The objective of this paper is to answer some of the policy relevant questions to the management of environmental invasive plants in general and the Californian thistle in New Zealand in particular. The results of this paper can be used particularly when there is stochasticity in the effect of a biological control agent on the target plants. To address this issue, we first describe the problem and study area followed by policy issues regarding the management of Californian thistle. Then we present the model. In the model section, we first present the deterministic model and then introduce the stochastic model in an empirical setting. Finally we discuss the results and present some conclusions.

2. Californian thistle in New Zealand

The Californian thistle (*Cirsium arvense*) is a widespread, aggressive, perennial weed of pastures, rangelands, and other agricultural land (Skinner *et al*., 2000; Morishita, 1999; and Donald, 1990). This thistle is found in both perennial and annual crops in Eurasia and America, as well as New Zealand and it is considered one of the "world's worst weeds" (Friedli and Bacher, 2001). New Zealand is a country with a very diverse and valuable natural resource base that is widely invaded by Californian thistle causing severe environmental problems (Bourdôt *et al.*, 2004; and Bascand and Jowett, 1982).

The damages caused by weeds here have been estimated to be millions of dollars annually (Harris, 2002). Therefore it is important to find the best control strategy to reduce the damage caused by this invasive weed. We consider seven possible control options to control Californian thistle in New Zealand. Furthermore, we analyze a combination of these control options which will result in 62 control strategies. The seven control options for controlling the thistle are the following.

2.1. Applying MCPA. MCPA is a systemic herbicide that gives temporary control but severely damages nitrogen-fixing clovers in treated pasture. This herbicide is one of the most effective ways of quickly reducing thistle shoot density, and therefore can be important in increasing the production of the pasture (Barrons, 1969). In this study, benefits lost by removing clover are added to the price of MCPA.

2.2. Applying MCPB. MCPB is closely related to MCPA, but does not damage clovers.

2.3. Mowing in January. Mowing is a mechanical option for controlling Californian thistle. In this method the arms and knives of machines remove the thistle's foliage, which results in reduced root growth and reduced shoot production (Bourdôt *et al.,* 1998).

2.4. Mowing in March.. This is like the previous option, but mowing now occurs in March.

2.5. Over grazing. Grazing animals such as geese, goats, sheep, and cattle at sufficiently high intensity can control invasive species in rangelands. Sheep and goats are most commonly used for this purpose because they often eat plants rejected by cattle and horses. The grazing of weeds damages their physiology and controls their spread (Monaco *et al.,* 2001) and has been proven to be effective against Californian thistle (Hartley *et al.,* 1984).

2.6. Applying mycoherbicide. These are plant pathogens that can control weeds in a similar way to chemical herbicides (Charudattan, 1991; and Trujillo and Templeton, 1981).

2.7. Introducing weevil: phytophagous insects can be used as biological agent to control weeds. They usually come from the native habitat of the weed and must be extensively tested to ensure that they will not attack plants other than those being targeted (Pemberton, 2000). Such insects, once established, can often support their own growth and expansion. Here we consider the weevil, *Apion* *onopordi*, a putative biological control agent for Californian thistle which is considered for release in New Zealand. *Apion onopordi*, however, has a stochastic effect on the thistle.

Given the problem of the Californian thistle and control options the following policy questions are posed:

- Is it worth introducing the weevil (*Apion onopordi*), considering its stochastic effects?
- Which combination of control options is optimal?
- What are the possible costs if we exclude chemicals?
- Is eradication worth pursuing?

Olson *et al.* (2002) claimed that if the discounted expected growth rate of invasive species is more than one, eradication of weed is a better control strategy than reducing weed density to a lower level. Given the expected growth rate of the thistle (more than one) in this paper we examine if eradication is optimal for Californian thistle.

In order to find the answers to these policy questions we develop a stochastic dynamic programming model for Californian thistle management which will be discussed in the following sections.

3. The model

Weed control decisions have to be made each year and these decisions are subject to stochasticity. Therefore we set up a model to determine the combination of control options that maximizes the present value of expected net returns obtained from the pasture. The path of weed densities and control strategies for a planning period of 40 years are analyzed. Decisions for choosing the control strategies are made at the beginning of each year, based on the known weed density at the end of the previous year and expected effect of the insect on the growth rate and the density of the thistle. The effect of control strategies is observed only in the year of application except for the introduction of the weevil. Once the weevil has been introduced, it will remain active for the rest of the planning period and in reality it will have a stochastic effect.

In this section, first a deterministic dynamic programming model will be presented assuming that the weevil has a deterministic effect on the growth and the density of the thistle. Secondly, a stochastic optimization model will be presented taking the stochastic effect of the weevil into account.

3.1. Deterministic optimization model

The objective of the deterministic model is to choose a sequence of control strategies , u_t , that maximizes the present value of a stream of annual net benefits, V_t . Decision variable (u_t) is a discrete variable and corresponds to the control strategy adopted in year *t.* The number of control strategies that a decision maker can choose from is given by *ns,* where $1 \leq u_t \leq ns$ (See Table A.1. in the Appendix for an overview of control strategies). Note that the set of control strategies, $cs = \{1,...,ns\}$ can be subdivided into two subsets: $cs_{NI} = \{1,...,ns_{NI}\}$ and $cs_I = \{ns_{NI} + 1,...,ns\}$, with cs_{NI} the set of strategies that do not include the introduction of the weevil, and cs_I the set of strategies that do include the introduction of the weevil. ns_{NI} represents the number of strategies that do not include the introduction of weevil. Once one of the strategies from set cs_I has been adopted, the decision maker can only choose from set cs_{NI} in the subsequent years.

The optimization problem for year *t* is given in the following equation:

$$V_t(w_{t-1}) = \max_{u_t}\left[B_t(w_t, u_t) + \delta V_{t+1}(w_t)\right] \quad (1)$$

Subject to:

$$w_t = f(w_{t-1}, u_t), \quad (2)$$

where w_t represents the density of the thistle at the end of year *t* and δ represents the discount factor. In equation (1) the future net benefit, V_{t+1}, is affected by the density of the thistle shoots at the end of year *t*, w_t. The net benefits in year *t* are affected by the control strategy adopted in year *t*, u_t and the shoot density resulting from applying this strategy.

The net annual benefits of the pasture $B_t(w_t, u_t)$ in year *t*, are obtained from the following functions (Cousens, 1985):

$$B_t(w_t, u_t) = H_t(w_t) - C_t(u_t) \quad (3)$$

with,

$$H_t(w_t) = \frac{S \cdot \gamma}{g}\left(1 - \frac{\varsigma \cdot w_t}{100.[1 + (\varsigma \cdot w_t / \alpha)]}\right) \quad (4)$$

where, $H_t(w_t)$ are the benefits obtained from the pasture and $C_t(u_t)$ represents the costs of controlling the Californian thistle at time *t* which depend on the strategy chosen. In the benefit function, parameter *S* represents the monetary value of a livestock unit, *g* represents the amount of forage production used per livestock unit per year and γ represents the annual yield of dry matter (kg/m^2) in the absence of weed. The parameter ς represents the percentage of yield loss caused by Californian thistle shoots as the density of shoots approaches zero and α represents the percentage loss in yield as the density of the Californian thistle shoots approaches infinity.

Population dynamics of the thistle as presented in equation (2) are explained by the following logistic growth function:

$$w_t = L(u_t) \cdot r \cdot N(u_t) \cdot w_{t-1} \cdot (1 - \frac{w_{t-1} \cdot N(u_t)}{\mu}) + w_{t-1} \cdot N(u_t)\,, \quad (5)$$

Where $L(u_t)$ is a multiplier which indicates the effect of the control strategy, u_t, on the growth rate of the thistle. $N(u_t)$ is a multiplier vector that indicates the direct effect of the control strategy on the thistle density (see Table A.1 in appendix for the values of these parameters). For instance, for the first strategy where none of the control strategies are chosen ($u_t = 1$), the value of $N(u_t)$ and $L(u_t)$ are equal to one which means they have no effect on the benefit function. Control strategy number 11, for instance, reduces the growth rate to 70 percent of its initial value ($L(11) = 0.7$) and reduces the density of thistle to 18 percent of its initial value ($N(11) = 0.18$). Parameter μ represents the maximum density of the Californian thistle shoots that can grow on one square meter of land. The value of μ is constant and is not changed by control treatments. The parameter *r* represents the maximum rate of increase in Californian thistle shoot density and is influenced by the ecological conditions of a site. The introduction of the weevil, is assumed to reduce the growth rate (*r)* for all remaining years. No other control treatment changes the value of *r*. The impacts of the various control strategies and their costs are shown in Table A.1 in the appendix. Figure 1 shows the relationship between the Californian thistle shoot densities in year *t* as a function of the density in year *t+1* in the absence of any control treatment.

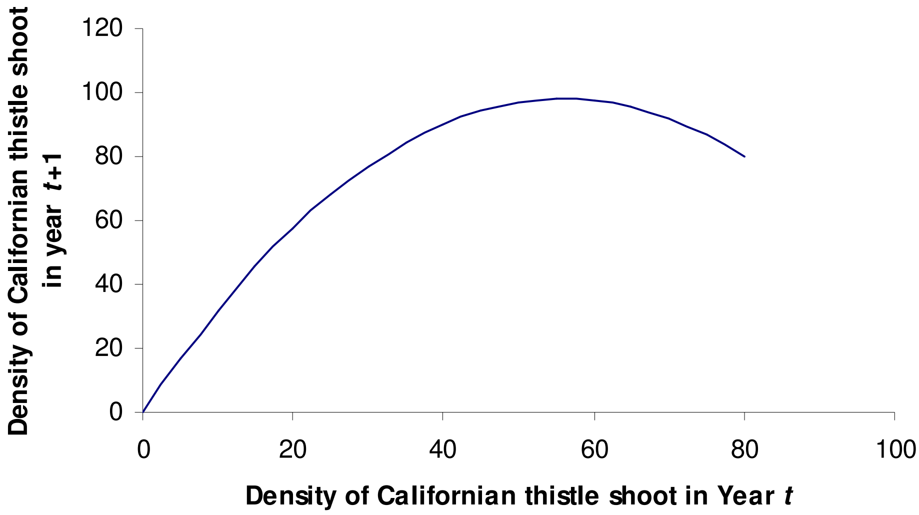

Figure 1 The dynamics of Californian thistle. The density of the thistle shoots in year (*t*+1) is given as a function of shoot density in year *t* as described by Equation (5) without control.

3.2. The stochastic optimization model

In the deterministic model that has been presented in the previous section, the efficacy of the weevil was assumed to be constant. However, the weevil could infect the host plant with lower rates due to some environmental factors and the resistance of the host plants (Derera, *et al.*, 2000; Reglinski *et al.,* 1997; Ortiz *et al.,* 1995; and Giga *et al.,* 1991). In this section, a stochastic optimization model is developed considering the stochastic effect of the weevil on the density and growth rate of the thistle.

The model stochasticity assumes a discrete number of states of nature, each with a known probability of occurrence and resulting in a different efficacy of the insect. At the beginning of each period *t*, (knowing thistle density at the end of period t-1) a decision has to be made with respect to the control strategy, u_t, that should be chosen. As the weevil has stochastic effects, benefits in year t as well as future benefits are stochastic.

To include the stochastic effects of the weevil on the growth rate we introduce a multiplier, $\Psi(u_t)$, which indicates the effect of the control strategy on the growth rate. The mean and standard deviation of Ψ depend on the control strategy. For the strategies that do not include the insect $\Psi(u_t) = L(u_t)$ as defined in equation (5). For strategies with the insect included, the expected effect of the strategy on the growth rate will be known, with $E\Psi(u_t) = L(u_t)$.

The efficacy of the weevil depends on the state of nature with a known probability distribution. In order to simulate the stochasticity, we assume discrete states of nature. For each period, t ,there are possible states of nature (1, …, I).

Each state of nature results in a different multiplier for the growth rate (Ψ) or the density (Φ). For the strategies that include the insect we have:

$$\Pr(\Psi(u_t) = \psi_i(u_t)) = p^{\psi}{}_i \tag{6}$$

for possible states of nature with i= 1, …, I.

The parameters $\psi_i(u_t)$ are the possible realizations of the growth rate multiplier Ψ. It follows that:

$$\sum_{i=1}^{I} p^{\psi}{}_i = 1 \text{ and } 0 \le p^{\psi}{}_i \le 1 \tag{7}$$

Because the multipliers of the growth rate and the density are stochastic, the growth function of the thistle (5) also becomes stochastic. Thistle density at the end of each period is a stochastic variable ($\overline{w_{i,t}}$) depending on a given density level at the end of period t-1 (w_{t-1}). Possible realizations of $\overline{w_{i,t}}$ are:

$$w_{i,t} = \psi_i(u_t) \cdot r \cdot N(u_t) \cdot w_{t-1} \cdot (1 - \frac{w_{t-1} \cdot N(u_t)}{\mu}) + w_{t-1} \cdot N(u_t) \tag{8}$$

for i=1, …, I.

As a result of this set up, it is not possible to determine net benefit for each strategy at the beginning of period *t*. Only expected net benefits can be determined, which are represented in the following equation:

$$EV_t(\overline{w}_{t-1}) = \underset{u_t}{Max}\{EB_t(\overline{w}_t, u_t) + \delta EV_{t+1}(\overline{w}_t)\} \tag{9}$$

For our case that the effect of weevil is stochastic this is equal to:

$$EV_t(w_{t-1}) = \underset{u_t}{Max} \sum_{i=1}^{I} p_i^{\psi} \left\{B_t(w_{i,t}, u_t) + \delta EV_{t+1}(w_{i,t})\right\} \tag{10}$$

with $w_{i,t}$ the density in period *t* if $\Psi(u_t) = \psi_i(u_t)$

Because u_t is a discrete variable it is not possible to solve the problem analytically. Therefore we solve the model numerically using backward induction. In the next section, we explain how the model is solved in more detail.

4. Data and algorithm

4.1. Parameter values

Parameter values are presented in Table 1 and Table A.1.

Table 1 Parameter values*

Parameter	Definition	Value
γ	Annual yield of dry matter (kg/m^2)	8.5
α	Percentage loss in yield as the density of the thistle shoots approaches infinity	100
r	Growth rate of the thistle	2.5
μ	Maximum density of the thistle shoots that can grow on one square meter	80
g	Forage production used per livestock unit per year (kg)	550
ς	Yield loss caused by the thistle as the density of shoots approaches zero (%)	5
S	Monetary value of a livestock unit (NZ$)	68.3
δ	Discount factor	0.97

* γ, α, r, μ and ς were obtained from personal communications (Bourdôt and Leathwick, 2006). Other parameters (g, S and δ) were calculated or obtained from financial budget manual (Burtt, 2004).

4.2. Control strategies and their efficacies

Seven possible control options are discussed in Section 2. Table A.1 shows a full matrix of all possible combinations (strategies) of these seven control options. The rows of this matrix represent the strategies and the columns are the control options. The values in this matrix were set to 0 or 1 with a value of zero indicating that the corresponding option is not included in the strategy while 1 means that the particular control option is included. For instance, in strategy 1 in which all values of the row are zero, no control option is applied. In strategy 16 control options number 1 and 5 were set to 1 the others to zero, indicating that this strategy is a combination of MCPB and mowing in March.

All possible combinations of control options yield 128 potential strategies. But some of the strategies are not logical and are therefore excluded. For example two different herbicides (MPCA, and MPCB) and mowing in January, have the same time of application. Practically, applying two types of herbicides at the same time or combining them simultaneously with mowing is not logical, because there will be no additive effect of the combination. Excluding all illogical strategies results in a final matrix of 62 strategies.

To determine the values of the strategy efficacy vectors *N* and *L*, each element of the control strategies was itself first allocated an efficacy (shown in row 2-8 in Table A.1), which were based on published data (Table A.1 appendix). For strategies with a combination of control options, the efficacies were taken from published data when available. In the absence of empirical data the strategy efficacy values were calculated assuming that the actions of the component options were independent and multiplicative. Thus for strategy 9 (MCPA + mowing in January), the proportion of thistle shoots surviving both treatments was $N = 0.26 \times 0.5 = 0.13$ (see Table A.1).

4.3. Probability distribution for efficacy of the weevil

The efficacy of the weevil has a normal distribution with mean 0.7 and standard deviation of 0.35 (Bourdôt and Leathwick, 2006). In order to avoid multiplier values less than 0.4 or larger than one, which would result in unrealistically low growth rate or a multiplier value exceeding 1, a conditional normal distribution is adopted allowing only values of $\psi_i(u_t)$ between 0.4 and 1.

An often used simulation in stochastic models is to randomly draw a number of possible realizations of the stochastic variable from a continuous probability distribution. However this method has a disadvantage, because each time the model is solved, the possible efficacies of biological control realizations get different values. This may lead to different results and makes it difficult to compare scenarios with each other. To solve this problem we introduce *I* discrete states of nature, $i=\{1, \ldots, I\}$ each resulting in discrete values for the insect efficacy and each with a known probability of occurrence.

To determine the probability of occurrence for each state of nature, intervals of multiplier values are considered. As a sensitivity analysis showed that the precision of the results does not change if the interval size becomes less than 0.05, interval size of 0.05 have been adopted.

The probability for each efficacy of the weevil will be calculated by the following equation:

$$p^{\psi}{}_i = \Pr(\Psi(u_t)) = \psi_{i,t} = \frac{F(\psi_{i,t} + \Delta) - F(\psi_{i,t} - \Delta)}{F(1) - F(0.4)} \qquad (11)$$

with,

$$\Delta = \frac{\psi_{i,t} - \psi_{i-1,t}}{2} = 0.025 \text{ for } i \in \{2, ..., I\} \qquad (12)$$

F is the cumulative probability function of the normal distribution. In order to have maximum cumulative probability of one, $F(\psi_{i,t} + \Delta) - F(\psi_{i,t} - \Delta)$ is divided by *F(1)-F(0.4).* As a result:

$$\sum_{i=1}^{I} p^{\psi}{}_i = 1 \text{ and } 0 \le p^{\psi}{}_i \le 1 . \qquad (13)$$

Table 2 represents the values of ψ_i and $p^{\psi}{}_i$, and Figure 2 shows probability distribution for weevil efficacy.

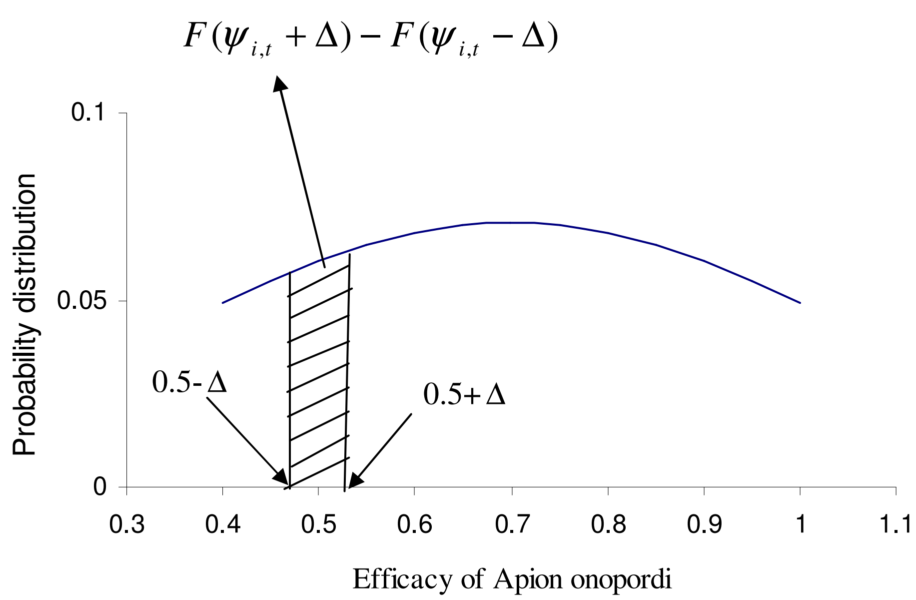

Figure 2. The probability distribution for efficacies of the weevil.

Table 2 Efficacies of the weevil and probabilities of each occurrence.

Efficacy of the weevil and probabilities of their occurrence	
Efficacies (ψ_i)	Probabilities (%) $p_i^{\psi} = \Pr(\Psi = \psi_i)$
0.4	4.91
0.45	5.49
0.5	6.02
0.55	6.46
0.6	6.80
0.65	7.01
0.7	7.08
0.75	7.01
0.8	6.8
0.85	6.46
0.9	6.02
0.95	5.49
1	4.91

4.4. Solving the optimization model

The model is solved using backward induction by MATLAB. As the insect can be effective from the moment of introduction till the end of the planning period, the backward induction algorithm implies that we have to solve two models. In the first model it is assumed that in period 1 a control option is adopted which includes the introduction of the insect. As a result in other periods the insect will not be adopted anymore, but the growth rate will depend on the stochastic effect of the insect. In the second model in all 40 periods only the control strategies can be adopted that do not include the insect. The latter model is not stochastic because the effects of the other control strategies are assumed to be certain. First backward induction is set up as follows.

For a discrete number of weed densities the model is solved for the final period *(t=40)*. The optimal control strategies for period 40 are determined by optimizing the expected benefit for period 40, for a given thistle density at the end of period 39, w_{39}, and for a given probability distribution of the efficacy of the insect. Secondly, for period 39, for a discrete number of possible densities at the end of period 38, w_{38}, the optimal control strategy for period 39 is determined by maximising expected benefits for the remaining period, $\delta EV_{40}(\overline{w_{39}})$, plus expected benefit for the current period, $EB_{39}(\overline{w_{39}}, u_{39})$. Possible realizations of V_{40} can be determined using the results from the previous step. Values of $w_{i,39}$ for which $\delta EV_{40}(\overline{w_{39}})$ has not been determined in the previous step are estimated using linear interpolation. For the rest of the period the procedure is the same as period 39. However 39 is replaced by *t* and 40 by *t+1*.

5. Scenarios and results

In this section, we discuss the effect of the stochastic efficacy of the weevil on the control strategy chosen. To analyse these effects we distinguish three scenarios (see Table 3). Moreover, chemicals as weed control options have the risk of contaminating food and drink and they can damage the environment. Therefore some users prefer not to apply them (Reid *et al.*, 2007). As chemicals could be more cost efficient and beneficial from an economic point of view we want to evaluate the exact effect on the net benefits of the pasture of excluding these control options. Therefore two sub scenarios are derived from each scenario (see Table 3).

Table 3 Definition of scenarios.

	With MCPA and MCPB	Without MCPA MCPB
Deterministic model	D_C	D_{CN}
Model with stochastic efficacy of weevil	$S_{w,C}$	$S_{w,CN}$

In Scenario D_C and D_{CN} the efficacy of all control strategies are assumed to be known with certainty. Scenario $S_{w,C}$ and $S_{w,CN}$ represent the results of the stochastic model, in which weevil introduction has a stochastic effect on thistle growth. In the above mentioned scenarios index “C” refers to the sub scenarios in which chemicals (MCPA and MCPB) are included and index "CN" refers to the sub scenarios in which chemicals are not included. For all scenarios and sub scenarios we compare the NPV and the thistle density of the optimal strategies.

5.1 Transition of the thistle density between year t and year t+1

The optimal control problem is autonomous which means that the state transition equation does not depend on the time period. For each year, except for the years in which the choice has to be made whether or not to introduce the weevil, optimal control strategies only depend on the current thistle density and not on control strategies that were chosen in the previous period. Using the optimal decision rule provides an optimal state transition. For Scenario $S_{w,C}$ and $S_{w,CN}$ the optimal transition, i.e. the relationship between the state at time t and the state at time t+1, under optimal management is shown in Figure 3. Only these transition relationships are shown as all scenarios, which show only a zero to 0.02 differences in the density transitions. These small differences show that the stochastic effect of the weevil has a very small effect on the thistle density.

Figure 1 shows that without control treatments, the thistle population rapidly increases. In contrast, the application of optimal control strategies results in the maintenance of low thistle densities and the quick reduction of density if the initial thistle density is high. Figure 3 shows, for the sub-scenarios with chemicals, if the initial density of the thistle is lower than 50 shoot/m^2, the density of thistle in year *t+1* is slightly higher in these scenarios than in the sub-scenarios without chemicals. For initial densities exceeding 50 the reverse is true. By excluding chemicals, more control options are needed. For higher densities, however, chemicals are more cost effective and can more easily keep the thistle density at a lower level.

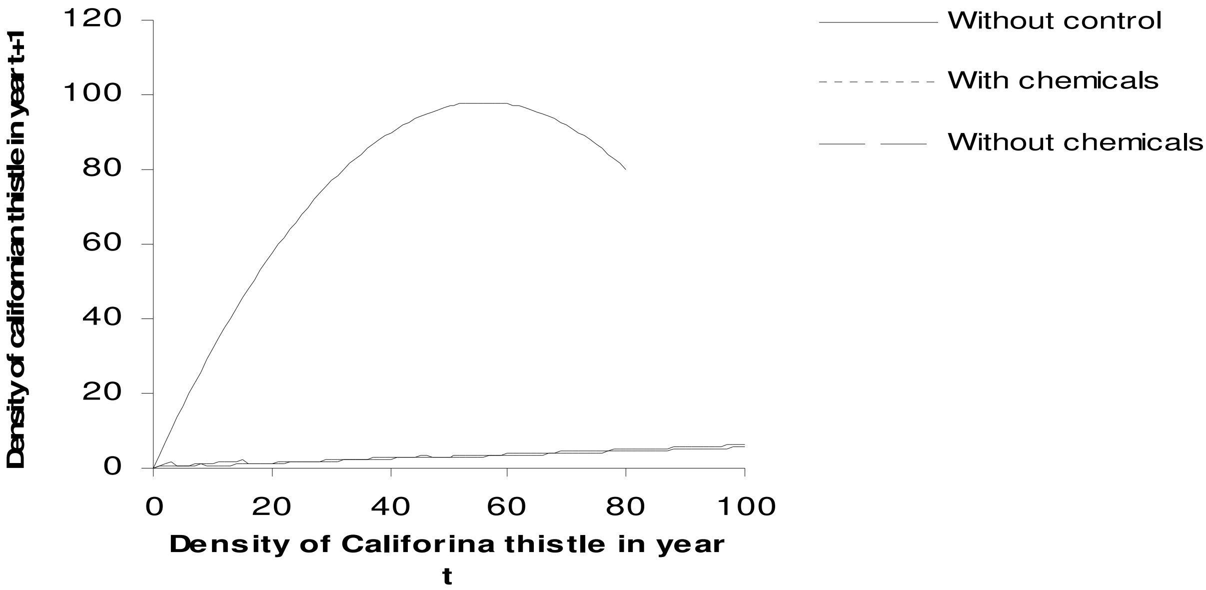

Figure 3 Changes in Californian thistle shoot population density under optimal strategies, for Scenario $S_{w,C}$ and $S_{w,CN}$ in case no control strategy is adopted.

As we can see in Figure 3, in contrast to Olson *et al.*, (2002) densities will never reach zero, even though they will become small in only few years. The efficacies of control strategies (see Table A.1) show that there is no control strategy that reduces the thistle density by 100 percent, and therefore eradication is not a viable strategy.

5.2 The optimal strategies

The optimal strategies for the different scenarios are presented in Table 4. It shows that the optimal strategies for Scenario D_C are the same as for Scenario $S_{w,C}$, and the optimal strategies for Scenario D_{CN} are the same as for Scenario $S_{w,CN}$. This means that the optimal strategy for the deterministic case is similar to the optimal strategy in the case where the effect of weevil is stochastic. Even though the target plants can be resistant to the weevil (Derera *et al.*, 2000; Ortiz *et al.,* 1995; and Giga *et al.,* 1991) and its efficacy is stochastic, the costs of introducing weevil are so low as compared to other control options, that no change is observed in the optimal strategies. Moreover, weevil is the only control option which once introduced can compensate a low efficacy in one year with a possible high effect in another year.

These results are in contrast with some arguments against the introduction of weevil, as some think that weevil is not worth introducing because of its stochastic impact. Its low costs and long-run effect, however, make it a very attractive control option as long as it is not causing a significant negative external effect to the ecosystem.

Table 4 Optimal starting strategies for different ranges of initial thistle density for the deterministic model and stochastic models. Chemicals are either included or excluded .*

Initial Californian Thistle density (shoots/m^2)	With chemicals		Without chemicals	
	Scenario D_C		Scenario D_{CN}	
	Number	Strategy	Number	Strategy
0.00-1	8	Insect	8	Ins.
1-3	39	Ov.Gr., Ins.	40	Mo.J. Ov.Gr., Ins.
3-5	14	MCPA, Ov.Gr., Ins.	29	Myc., Mo.J., Ov.Gr., Ins.
5-17	14	MCPA, Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.
17-49	15	MCPA, Mo.J. Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.
49-100	55	MCPA, Myc., Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.
	Scenario $S_{w,C}$		Scenario $S_{w,CN}$	
	Number	Strategy	Number	Strategy
0.00-1	8	Insect	8	Ins.
1-3	39	Ov.Gr., Ins.	40	Mo.J. Ov.Gr., Ins.
3-5	14	MCPA, Ov.Gr., Ins.	29	Myc., Mo.J., Ov.Gr., Ins.
5-17	14	MCPA, Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.
17-49	15	MCPA, Mo.J. Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.
49-100	55	MCPA, Myc., Ov.Gr., Ins.	62	Myc.,Mo.M. Mo.J., Ov.Gr., Ins.

*Myc (mycoherbicide), Mo.M (mow in March), Mo.J (mow in January), Ov.Gr. (overgraze), Ins. (weevil).

In Table 4, the optimal strategies for a range of possible initial densities of the thistle are given. Two observations can be made from this. Firstly, the higher the initial thistle density the more control options are needed to keep the density of the thistle at an optimal level. For high densities of the thistle the marginal economic damages of the thistle are higher than the costs of additional control options. Secondly, for the sub-scenarios without chemicals (D_{CN} , $S_{w,CN}$) more than one control option is needed to substitute one chemical control option. This is because the application of chemicals is more effective than the non-chemical control options. Thirdly results show that mycoherbicide is a good alternative for the use of MCPA and MCPB. In the sub-scenarios without chemicals, mycoherbicide is applied at a much lower density levels than in sub-scenarios with chemicals, even when stochasticity is included.

The NPVs (NZ$/ha) for the various scenarios for a range of initial densities of thistle are presented in Table 5. Comparing the NPV of the stochastic and deterministic model, it can be seen that when the stochastic effect of the weevil is included in the model, the NPV obtained from the pasture is the same as the deterministic scenario. Because the cost per hectare of introducing the weevil is low and the weevil only affects the growth rate of the thistle. Table 5 also shows that when chemicals are excluded from the control strategies a slightly lower NPV is obtained. This reduction in NPV becomes larger as thistle density increases. As explained above, for higher densities of thistle, chemicals become more cost effective.

Table 5 shows that effects of excluding chemicals on the NPV are low. It can be concluded that replacing chemicals by more environmentally friendly options can easily be done at low costs.

Table 5 NPV(NZ$/ha) for selected initial thistle densities for the deterministic model and stochastic models. Chemicals are either included or excluded .*

Initial Californian thistle density	NPV when chemicals are included (NZ$/ha)	NPV when chemicals are excluded (NZ$/ha)	Percentage decrease in NPV when chemicals are excluded
	Scenario D_C	Scenario D_{CN}	
1	23341	23341	0
5	23170	22987	0.8
10	23119	22877	1.1
20	23039	22724	1.4
40	22952	22578	1.6
60	22880	22476	1.8
80	22821	22394	1.9
	Scenario $S_{w,C}$	Scenario $S_{w,CN}$	
1	23341	23341	0
5	23170	22987	0.8
10	23119	22877	1.1
20	23039	22724	1.4
40	22952	22578	1.6
60	22880	22476	1.8
80	22821	22394	1.9

5.3. Sensitivity analysis

We conducted a sensitivity analysis to examine the effects of variations of parameter values on the optimal strategy chosen. Table 6 shows for which variations in parameter values optimal strategies do not change. Of course NPV slightly changes if parameter values change.

Table 6 Parameter deviations (%) and the range of their change that do not affect the optimal strategy.*

Parameter	Deviations (%)	Range
γ	18	6.9-10
α	50	50-100
r	8	2.3-2.7
μ	40	48-112
g	20	440-660
ς	20	4-6
S	20	55-89
δ	85	0.15-1.8
C	15	Depend on the strategy
N 1	10	Depend on the strategy
N 2	40	Depend on the strategy
L	14	Depend on the strategy

* γ (annual yield of dry matter (kg/m^2)), α (percentage loss in yield as the density of the thistle shoots approaches infinity), *r (*growth rate of the thistle), μ (maximum density of the thistle shoots that can grow on one square meter), *g* (forage production used per livestock unit per year (kg),), ς (Yield loss caused by the thistle as the density of shoots approaches zero(%)). *S* (monetary value of a livestock unit (NZ$)), δ (discount factor), N 1 (density efficacy for strategies 2-8), N2 (density efficacy of a singe control option within the control strategies 9-62) and L (growth rate efficacy).

The sensitivity analysis shows that firstly the growth rate of the thistle has the strongest effect on the results because the growth rate influences the thistle density which has a large impact on the benefit obtained from the pasture. Secondly, most of the non-economic parameters such as γ, α, μ, *g*, and ς,that are influenced by conditions of the site, have a low impact on the strategy chosen. Thirdly, efficacies of the control options have a low impact on the strategy chosen. This impact is lower when the control option is combined with other options, because when one control option is combined with other options, variation is absorbed by the other control options. For example the application of MCPA alone reduces the thistle density by 74 percent (strategy number 2) but when it is combined with mycoherbicide, mowing in March and over grazing (strategy number 53) the additive efficacy of

MCPA is only 4.2 percent. Fourthly, variations in the economic parameters (C and δ) have a very low effect on the strategy chosen particularly discount factor (δ). We conclude that within the ranges of our sensitivity analysis the model is robust against changes in the parameter values.

6. Summary and conclusions

We obtained a solution to an invasive species management problem which considered the stochastic effect of biological control treatment (the insect). We applied a stochastic dynamic programming approach for controlling Californian thistle in pastures in New Zealand. This model helps us to answer the following questions that were raised in Section 2:

1. Is it worth introducing the weevil (*Apion onopordi*) , considering its stochastic effects?
2. Which combination of control options is optimal?
3. What are the possible costs if we exclude chemicals?
4. Is eradication worth pursuing?

Regarding the first question, we found that despite of the possible resistance of host plants to weevil (Derera, *et al*., 2000; Ortiz *et al.,* 1995; and Giga *et al.,* 1991) that result in its stochastic efficacy, it is still optimal to introduce weevil to the pastures in New Zealand assuming it has no adverse effect on other species.

Regarding the second question, the analysis indicates that when chemicals are included, for most ranges of thistle densities (densities between 5 to 61 shoot/m^2) the best control strategies are to apply MCPA, overgrazing and introduction of weevil (number 14) and MCPA, mowing in January, overgrazing and introduction of weevil (number 15). It is also shown that when chemicals are excluded, for most densities (densities more than 8 shoot/ m^2), the best strategy is to apply mycoherbicide, mowing in March, mowing in January and overgrazing (number 62).

Regarding the third question the model shows that excluding chemicals and using more environmentally friendly options reduce NPV by a maximum of 1.3 percent.

Regarding to the forth question the results show that total eradication, as found to be optimal by Olson *et al*. (2002), is not pursued in our case. Note that there are no control options that allow for total eradication, making the conclusion of Olson *et al.* (2002) rather theoretical.

Finally, the results show that the stochasticity of the efficacy of the insect does not affect the optimal control measure adopted.

Our analysis demonstrates how stochastic dynamic programming offers a useful framework for management of invasive species that include stochastic parameters. We concluded that the stochastic efficacy of biological control agent does not change the optimal control strategy adopted under current setting in the model. The biological control agent can be applied at very low cost and it remains attractive to be used, even under a stochastic setting. In further research we will investigate whether stochastic impacts in other control options will affect the results.

Acknowledgments

We are grateful to Dr Graeme Bourdôt and Dave Leathwick for providing valuable data. We thank Prof. Anton Meister for providing contacts and facilities at Massey University in New Zealand. We thank Elena Saiz and Eligius Hendrix for their valuable comments on the programming in MATLAB.

Appendix 1.

Table A.1 near here

References

Bascand, L.D., Jowett, G.H., 1982. Scrubweed cover of South Island agricultural and pastoral land 2. Plant distribution and managerial problem status. *New Zealand Journal of Experimental agriculture* 10, 455-492.

Bourdôt, G.W., Hurrell, G.A. and Saville, D.J., 2004. Wounding of *Cirsium arvense* enhances the efficacy of *Sclerotinia sclerotiorum* as a mycoherbicide. *New Zealand Plant protection* 57, 292-297.

Bourdôt, G.W. and Leathwick, D. 2006. Personal communications.

Bourdôt, G.W., Leathwick, D.M., Hurrell, G.A. and Saville, D.J., 1998. Relationship between aerial shoot and root biomass in Californian thistle, *Proceedings of the 51st New Zealand Plant Protection Conference;* 11-13 August, 1998, Hamilton, pp. 28-32.

Bulte, E.H. and van Kooten, C. G. 1999. Metapopulation dynamics and stochastic bioeconomic modelling. *Ecological Economics 30, 293-299.*

Burtt, S.E., 2004. *Financial Budget Manual*. Canterbury, New Zealand.

Charudattan, R., 1991. The mycoherbicide approach with the plant pathogens. In: TeBeest, D.O. (Editor), *Microbial Control of Weeds*. Chapman & Hall, Washington D.C., pp. 25–27.

Cousens, R. A., 1985. Simple model relating yield loss to weed density. *The annals of applied biology* 107, 239-252.

Derera, J., Denash Giga, P. and Pixley, K.V., 2000. Resistance of maize to the maize weevil: II. non-preference. *African Crop Science Journal* 9, 441-450.

Donald, W.W., 1990. Management and control of Canada thistle (*Cirsium arvense*). *Reviews of Weed Science* 5, 193-250.

Ehler, L.E., 1998. Invasion biology and biological control. *Biological control 13, 127-133.*

Friedli, J.R. and Bacher, S., 2001. Direct and Indirect Effects of a Shoot-Base Boring Weevil and Plant Competition on the Performance of Creeping Thistle, Cirsium arvense,. *Biological Control* 22, 219–226.

Giga, D.P. and Mazarura, U.W. 1991. Levels of resistance to the maize weevil, *Sitophilus zeamais* (Motsch.) in exotic, local open-pollinated and hybrid maize germplasm. *Insect Science and its Application*s 12, 159-169.

Gomez, L.A., Rodriguez, J.G., Poneleit, C.G. and Blake, D.F., 1982. Preference and utilisation of maize endosperm variants by the rice weevil. *Journal of Economic Entomology* 75, 363-367.

Harris, G. (***2002). Invasive New Zealand weeds.* Journal of the Royal New Zealand Institute of Horticulture** ***5, 6-8***.

Hartley, M.J., Lyttle, L.A. and Popay, A.I., 1984. Control of Californian thistle by grazing management*, Proceedings of the 37th New Zealand Weed and Pest Control Conference*; 14-16 August 1984, Christchirch, New Zealand, pp. 24-27.

Higgins, S.I., Turpie, J.K., Costanza, R., Cowling, R.M., Le Maitre, D.C., Marais, C. and Midgley, G.F., 1997. An ecological economic simulation model of mountain fynbos ecosystems dynamics, valuation and management. *Ecological Economics* 22, 155-169.

Hill, G., and Greathead, D., 2000. *Economic evaluation in classical biological control.* In: Perrings, C., Williamson, M., Dalmazzone, S. (Editors) The Economic of Biological Invasions. Edward Elgar, Cheltenham, UK, pp. 208-223.

Hurrell, G. A., Bourdôt, G. W. and Saville D. J. 2001. Effect of application time on the efficacy of *Sclerotinia sclerotiorum* as a mycoherbicide for *Cirsium arvense* control in pasture. *Biocontrol Science and Technology 11, 317-330.*

McEvoy, P. and Cox, C., 1991. Successful biological control of ragwort, *Senecio jacobaea*, by introduced insects in Oregon. *Ecological Applications 4, 430-442.*

McFadyen, R.E., 1998. Biological control of weed. *Annual review of Entomology 43, 369-393.*

Monaco, J.T., Weller, C.S. and Floyd, A.M., 2001. *Weed Science Principals and Practices*. New York, Wiley.

Morishita, D.W., 1999. *Canada thistle*. In: R.L. Sheley and J.K. Petroff, (Editors), *Biology and Management of Noxious Rangeland Weeds*, Oregon State University Press, Corvallis, pp. 162–172.

Odom, D.I.S., Cacho, O.J., Sinden, J.A. and Griffith, G.R., (2003). Policies for the management of weeds in natural ecosystems: the case of scotch broom (*Cytisus Scoparius, L.*) in an Australian national park, *Ecological Economics 44, 119-135.*

Olson, L. J. and Santanu, R. 2002. The economics of controlling a stochastic biological invasion. *American Journal of Agricultural Economics 5, 1311-1316.*

Ortiz, R., Vuylsteke, D., Dumpe, B., and Ferris, R. S. B., 1995. Banana weevil resistance and corm hardness in *Musa* germplasm. *Euphytica* 86, 95-102.

Pandey, S. and Medd, R.W. 1991. A stochastic dynamic programming framework for weed control decision making: an application to *Avena fatua* L. *Agricultural Economics 6, 15-128.*

Pemberton, 2000. Predictable risk in weed biocontrol. Oecologia 125, 489-494.

Pimentel, D. (Editor) 2002. *Biological invasion economics and environmental costs of alien plant, animal, and microbe species*. Boca Raton, FL, USA; CRC Press, pp. 384-398.

Reid, M., Edwards, N., Sturgeon, K., and Murray, V., 2007. Adverse health effects arising from chemicals found in food and drink reported to the national poisons information centre (London), 1998-2003). *Food control 18, 783-787.*

Sheppard, A.W., Hill, R., DeClerck-Floate, R.A., McClay, A., Olckers, T., Quimby Jr. P. C. and Zimmermann, H.G., 2003. A global review of risk-benefit-cost analysis for the introduction of classical biological control agents against weeds: a crisis in the market? *Biocontrol News and Information 24 91N-108N.*

Skinner, K., Smith, L., Rice P., 2000. Using noxious weed lists to prioritize targets for developing weed management strategies. *Weed Science* 48, 640-644.

Thomas, M.B., and Willis, A.J., 1998. Biocontrol-risky but necessary? *Trends in Ecology and Evolution* 13, 325-329.

Trujillo, E.E. and Templeton, G.E., 1981. The use of plant pathogens in biological control of weeds, In Pimental, D. (Editor), *Handbook of Pest Management and Agriculture*, Vol. III. CRC Press, Boca Raton, pp. 345–350.

Table A.1 Controlling strategies, their efficacy and costs. The values of N and L were calculated from published data when available (see "Source" column), or were estimated by GWB[1] and DL[2] when published data was not available. Costs, C, were obtained from Fleming et. al. (2003). Myc (mycoherbicide), Mo.M (mow in March), Mo.J (mow in January), Ov.Gr. (overgraze), Ins (*Apion onopordi*).

Strategy	Control options							Efficacy		Cost ($NZ/ha)	Source
	1 MCPA	2 MCPB	3 Myc.	4 Mo.M.	5 Mo.J.	6 Ov.Gr.	7 Ins.	N	L		
1	0	0	0	0	0	0	0	1.00	1	0	
2	1	0	0	0	0	0	0	0.26	1	90.8	Hartley *et al.* (1984)
3	0	1	0	0	0	0	0	0.28	1	98	Hartley *et al.* (1984)
4	0	0	1	0	0	0	0	0.40	1	115	Hurrell *et al.*.(2001)
5	0	0	0	1	0	0	0	0.57	1	75	Bourdôt *et al.*.(1998)
6	0	0	0	0	1	0	0	0.50	1	75	Bourdôt *et al.*.(1998)
7	0	0	0	0	0	1	0	0.29	1	34	Hartley *et al.* (1984)
8	0	0	0	0	0	0	1	0.68	0.7	3	Friedli and Bacher(2001)
9	1	0	0	0	1	0	0	0.13	1	165.8	GWB and DL
10	1	0	0	0	0	1	0	0.08	1	124.8	GWB and DL
11	1	0	0	0	0	0	1	0.18	0.7	93.8	GWB and DL
12	1	0	0	0	1	1	0	0.04	1	199.8	GWB and DL
13	1	0	0	0	1	0	1	0.09	0.7	168.8	GWB and DL
14	1	0	0	0	0	1	1	0.05	0.7	127.8	GWB and DL
15	1	0	0	0	1	1	1	0.03	0.7	202.8	GWB and DL
16	0	1	0	0	1	0	0	0.14	1	173	GWB and DL
17	0	1	0	0	0	1	0	0.08	1	132	Hartley *et al.* (1984)
18	0	1	0	0	0	0	1	0.19	0.7	101	GWB and DL
19	0	1	0	0	1	1	0	0.04	1	207	GWB and DL
20	0	1	0	0	1	0	1	0.10	0.7	176	GWB and DL
21	0	1	0	0	0	1	1	0.06	0.7	135	GWB and DL
22	0	1	0	0	1	1	1	0.03	0.7	210	GWB and DL
23	0	0	1	0	1	0	0	0.20	1	190	GWB and DL
24	0	0	1	0	0	1	0	0.12	1	149	GWB and DL
25	0	0	1	0	0	0	1	0.27	0.7	118	GWB and DL
26	0	0	1	0	1	1	0	0.06	1	224	GWB and DL
27	0	0	1	0	1	0	1	0.14	0.7	193	GWB and DL
28	0	0	1	0	0	1	1	0.08	0.7	152	GWB and DL
29	0	0	1	0	1	1	1	0.04	0.7	227	GWB and DL
30	0	0	0	1	1	0	0	0.29	1	150	Bourdôt *et al.*.(1998)
31	0	0	0	1	0	1	0	0.17	1	109	GWB and DL
32	0	0	0	1	0	0	1	0.39	0.7	78	GWB and DL
33	0	0	0	1	1	1	0	0.08	1	184	GWB and DL
34	0	0	0	1	1	0	1	0.20	0.7	153	GWB and DL
35	0	0	0	1	0	1	1	0.11	0.7	112	GWB and DL
36	0	0	0	1	1	1	1	0.06	0.7	187	GWB and DL
37	0	0	0	0	1	1	0	0.15	1	109	GWB and DL
38	0	0	0	0	1	0	1	0.34	0.7	78	GWB and DL
39	0	0	0	0	0	1	1	0.20	0.7	37	GWB and DL
40	0	0	0	0	1	1	1	0.10	0.7	112	GWB and DL
41	1	0	1	0	0	0	0	0.10	1	205.8	GWB and DL
42	0	1	1	0	0	0	0	0.11	1	213	GWB and DL
43	0	0	1	1	0	0	0	0.23	1	190	GWB and DL
44	1	0	1	0	1	0	0	0.05	1	280.8	GWB and DL
45	1	0	1	0	0	1	0	0.03	1	239.8	GWB and DL
46	1	0	1	0	0	0	1	0.07	0.7	208.8	GWB and DL
47	0	1	1	0	1	0	0	0.06	1	288	GWB and DL
48	0	1	1	0	0	1	0	0.03	1	247	GWB and DL
49	0	1	1	0	0	0	1	0.08	0.7	216	GWB and DL
50	0	0	1	1	1	0	0	0.11	1	265	GWB and DL
51	0	0	1	1	0	1	0	0.07	1	224	GWB and DL
52	0	0	1	1	0	0	1	0.16	0.7	193	GWB and DL
53	1	0	1	0	1	1	0	0.02	1	314.8	GWB and DL
54	1	0	1	0	1	0	1	0.04	0.7	283.4	GWB and DL
55	1	0	1	0	0	1	1	0.02	0.7	242	GWB and DL
56	0	1	1	0	1	1	0	0.02	1	322	GWB and DL
57	0	1	1	0	0	1	1	0.02	0.7	250	GWB and DL
58	0	0	0	1	1	1	1	0.06	0.7	187	GWB and DL
59	0	0	1	1	1	1	0	0.03	1	299	GWB and DL
60	0	0	1	1	1	0	1	0.08	0.7	268	GWB and DL
61	0	0	1	1	0	1	1	0.01	0.7	227	GWB and DL
62	0	0	1	1	1	1	1	0.02	0.7	302	GWB and DL

[1] Bourdôt, G.W.
[2] Leathwick, D.