Optimal Integrated Strategies to Control an Invasive Weed*

Morteza Chalak¹ and David J. Pannell²

¹Centre for Environmental Economics and Policy, School of Agricultural and Resource Economics, University of Western Australia, 35 Stirling Highway, Perth, WA, 6009, Australia (corresponding author: phone: +61-8-64885508; fax: +61-8-64881098; e-mail: morteza.chalak@uwa.edu.au).

²Centre for Environmental Economics and Policy, School of Agricultural and Resource Economics, University of Western Australia, 35 Stirling Highway, Perth, WA, 6009, Australia (phone: +61-8-64884735; fax: +61-8-64881098; e-mail: david.pannell@uwa.edu.au).

---

* Published as: Chalak, M. and Pannell, D.J. (2015). Optimal integrated strategies to control an invasive weed, *Canadian Journal of Agricultural Economics* 63(3), 381-407.

Abstract:

Although there have been numerous studies on the economics of weed control in agriculture, relatively few studies have focused on weeds in natural ecosystems. A stochastic dynamic simulation model and a stochastic dynamic programming model are developed to: A) identify the combination of control options that is optimal for blackberry (*Rubus anglocandicans*) in Australian natural ecosystems, B) assess whether an integrated control strategy is superior to chemical-only strategies, C) evaluate the net benefits of biological control (a rust and grazing by goats), D) determine how changes in model parameters affect the optimal control strategy. The results indicate that, while an integrated strategy combining chemical and non-chemical control methods may be optimal in certain circumstances, it is not necessarily superior to a chemical-dominant strategy in all cases. The results show that grazing goats for control of blackberry can be optimal despite uncertainty about its effectiveness. Policy makers need to be aware of the tradeoffs between choosing more effective control options that may impose environmental and health risks versus less effective control strategies that are safer to the environment and human health.

Keywords: Environment; Economics; Weed; Stochastic; Optimization; Management

1. Introduction

In many environments, invasive species are significant threats to biodiversity, natural ecosystems and agriculture. Weeds are the most costly invasive species, leading to huge worldwide economic damages (Sheppard et al 2003). Weeds reduce water-management efficiency and natural biodiversity (Tyser and Key 1988; Fernandez 2011).

This study analyses optimal strategies to deal with blackberry (*Rubus anglocandicans*) in the environment. Vere and Dellow (1984) estimated that, in central western NSW (New South Wales), the value of lost production plus the cost of controlling blackberry was \$4.7m per year. James and Lockwood (1998) estimated that, across Australia, the cost of controlling blackberry plus the lost agricultural production was \$41.5m per year. Blackberry has invaded large areas of Victoria and Tasmania, eastern parts of NSW and southern parts of Western Australia, South Australia, and Queensland. Blackberry also infests many natural ecosystems in the United States (Pemberton 2000), New Zealand (Qinn, 1997), Latin America (Barreto, 2009) and Australia (Anonymous 2006), the focus of this study. Blackberry is also a threat to the Canadian natural environment (Cogliastro, 2006). Himalayan blackberry (*Rubus armeniacus*), a close relative of *Rubus anglocandicans*, is one of the most troublesome invasive species in Canada (Sy et al 2009). Blackberry invasion in natural areas reduces social welfare by reducing plant biodiversity in the infested area.

Blackberry is categorized as a Weed of National Significance (WoNS) in Australia due to its high invasiveness, its current extent and potential area of spread and its economic, environmental and social impacts¹. It is the highest ranked WoNS

---

¹ Criteria for selection of Weeds of National Significance are provided in <http://www.weeds.org.au/docs/WONSfactsheet.pdf> (accessed 2 April, 2013)

for southern Australia, our area of interest (Apan 2008; Weeds of National Significance 2009).

This study focuses on the control of blackberry in riparian areas because blackberry is attracted to high soil moisture and so occurs frequently in riparian areas (McDowell and Turner 2002). In addition, riparian areas often have relatively high environmental values (e.g. biodiversity, aesthetics, habitat) compared with other areas (Marczak et al 2010).

One aim of this paper is to identify the combination of blackberry control options that is optimal for use in natural areas in different circumstances. This information will assist state government agencies responsible for management of natural vegetation areas in southern Australia. We are particularly interested in the question of whether and in which circumstances Integrated Weed Management strategy is superior to chemical-only strategies. Secondly, we aim to evaluate the economic net benefits of the available non-chemical control methods: a rust fungus and grazing animals. Given their relatively low and uncertain efficacy, can they be cost-effective?

Although there have been a number of studies evaluating management strategies for weeds and other pests (e.g. Vere et al 2004; Eiswerth and van Kooten 2007; Llewellyn et al 2007; Fried et al 2012), there has not been an economic analysis of control strategies to deal with blackberry in the natural environment. Dynamically optimal weed control decision rules have been derived in a number of studies, including Wu (2001), Taylor and Burt (1984), Kennedy (1987), McConnachie et al (2003), Chalak-Haghighi et al (2008), and Chalak et al (2009). These studies have focused on weed control for agricultural benefits. However, this study is relatively innovative in that it studies the economics of weed spread to natural areas (Grimsrud et al 2008).

Studies that have considered the economics of environmental weeds and pests include Odom et al (2003), Cacho et al (2007), Cacho et al. (2008), (Sinden et al. 2008), Chock et al (2010), Epanchin-Niell and Hastings (2010), Hester et al (2010), Kaiser et al (2010) and (Giljohann et al 2011). Odom et al (2003), for example, studied optimal strategies to control scotch broom (*Cytisus scoparius*, L.) in an Australian national park. They studied the cost-effectiveness of management options including mechanical control, excluding tourists, chemical control, and biological control. They showed that the optimal control strategy depends on weed and seed density and that biological control is optimal in most circumstances. Cacho et al (2007)) developed a search and population-dynamics model to study the feasibility of eradicating an invasion. They showed that the success of an eradication program depends critically on the detectability of the target plant. Cacho et al (2008) analysed the optimal control for a woody perennial weed in a natural environment, comparing containment and eradication. They concluded that in the absence of a budget constraint, it may be desirable to eradicate invasions from relatively small areas. Sinden et al. (2008) studied the cost-effectiveness of a Threat Abatement Plan (TAP) to control bitou bush (*Chrysanthemoides monilifera* subsp. *rotundata* (DC.) T.Norl.) in Australia. They showed that the benefits of the TAP exceed its costs under a wide range of economic conditions.

These studies have generally examined only a small number of discrete control strategies, often only one. Integrated Weed Management (IWM) approaches that emphasise the use of several control measures (Buckley et al 2004; Pannell et al 2004; Chalak-Haghighi et al 2008) are often suggested to be the preferred way of controlling invasive weeds, relative to chemical-only strategies (e.g. Pardo et al 2010). This study tests this hypothesis, which has rarely been done for environmental weeds. A

methodological contribution of this paper is that, rather than considering a small number of strategies, we assess a comprehensive set of strategies, for the control of blackberry in Australia. A further methodological innovation is that we combine a spatial simulation model of weed spread with an optimisation model, allowing us to draw on the strengths of both methods.

This study is also original in its representation of two groups of decision variables. One group can be selected on an annual basis: chemicals, mowing and grazing by goats. The other group is a once-and-for-all action that is effective for a number of years, potentially forever. In this study, the latter category is relevant to the introduction of a rust fungus for the biological control of the weeds. Biological control options such as rust and grazing animals can be more environmentally friendly compared to chemicals (Ehler 1998; Thomas and Willis 1998; Pemberton 2000). However, environmental managers can be concerned about their cost-effectiveness due to the low and/or uncertain efficacy (Derera et al 2000; Hart 2001).

The next section of the paper describes the methods used, including the simulation model and the optimisation model. Results are presented and discussed for specific management strategies from the simulation model, and for the best strategy from the optimisation model. A detailed sensitivity analysis is undertaken, using the optimisation model. Finally, the conclusions from the study are presented.

2. Methods

A stochastic dynamic simulation model and a stochastic optimisation model are developed for southern Australia. The stochastic dynamic simulation model spatially simulates the spread of blackberry; measures spread of blackberry (results which are included in the optimisation model); measures the impact of control strategies on weed infestation; and calculates the overall net benefits for individual

strategies. The stochastic optimisation model uses blackberry spatial dynamics obtained from the simulation model; and applies stochastic dynamic optimisation to find optimal control strategies in different circumstances. Both models include estimates of the non-market environmental and social benefits of weed management in natural ecosystems.

The models represent the impact of blackberry on social welfare within 100m of a river in a region to which blackberry is well-adapted. Blackberries tend to infest areas adjacent to rivers and streams in relatively high-rainfall regions. Once established, they spread at a rate of around 1 to 2 metres per year.

Several different types of benefits could potentially be represented, including avoidance of losses from: (a) reduced biodiversity, (b) financial impacts on agricultural production, (c) reduced access to the river for swimming, and (d) reduced access to the river for fishing. Our focus is on category (a), represented by the non-market value of healthy vegetation. Category (b) is not included because of the study focuses on invasions on public lands.

Morrison and Bennett (2004) did estimate the non-market values of fishing and swimming for the Gwydir River in NSW, but the published estimates relate to an entire river basin, and reflect non-marginal impacts of blackberry infestation. For this study, the relevant values are marginal values, and there are reasons to expect that these will be small for any particular infestation. When a river becomes infested, blackberry does not occupy the entire riparian area, but instead typically leaves lengths of riverbank uninfested (Moore 2009). Thus, although blackberry may block access to the river for swimming and fishing in one place, it will be possible to access the river from another place nearby. We would expect this to substantially reduce the marginal benefits of blackberry removal in relation to fishing and swimming.

Therefore Categories (c) and (d) are not included because relevant information about these values is not readily available and they are likely to be small.

Benefits obtained from controlling blackberry due to increased health vegetation are represented by:

$$B_t = B_{veg}(w_t(u_t)) - c_t(u_t) \quad (1)$$

where u_t is the control strategy (the combination of treatments) adopted in year t , c_t is the cost of that control strategy and B_{veg} is the benefits obtained from healthy vegetation as a function of the extent of weed infestation (w_t), which is in turn a function of the control strategy used. All prices and costs are expressed in Australian dollars (\$).

2.1 Non-market values of blackberry impacts

Morrison and Bennett (2004) assessed the value of healthy vegetation as a percentage of the entire river margin with healthy vegetation. They showed that households in NSW are willing to pay \$1.98 as a one-off lump sum for a one per cent improvement in healthy riparian vegetation for the Gwydir River. We multiply the elicited values by the response rate of the survey (0.396), implicitly assuming non-respondents had zero valuation (in line with previous researchers, such as Byrnes et al. 1999; Ethier et al. 2000; Bergmann et al. 2008 and Longo et al. 2008). Given this assumption, for 2.65 million households in NSW, the marginal value (NPV) of a one per cent increase in healthy riparian vegetation along the Gwydir River comes to \$2,078,000.

We use this land value to calculate the social benefits per hectare from healthy riparian vegetation along the entire river, a length of 330 km (equivalent to 660 km on both river banks). The average width (distance from the river) on each side of the

river that has high potential to be infested by blackberry is estimated to be 100 metres (Gammie2009). Thus, the total area of healthy vegetation that can be infested by blackberry within the 330 km length totals 6600 ha. The estimated non-market value of \$2,078,000 relates to one per cent of the total area, or 66 ha. Thus the lump sum value of healthy vegetation is \$31,500 per ha, the equivalent of \$1900 per ha per year using a discount rate of 6%. Given high uncertainty about the broader relevance of any particular non-market valuation study, we later conduct comprehensive sensitivity analysis to test the impact of changing values on the selection of optimal strategy. As the policy makers are more concerned about which strategy to choose, the main focus of our sensitivity analysis will be on the selection of control strategies rather than the absolute values of net benefits.

2.2 Control Strategies

There are 8 control options considered for the control of blackberry: introduction of a rust (*Phragmidium violaceum*) and grazing goats as biological control agents, five herbicide options (glyphosate, glyphosate plus metsulfuron, metsulfuron (metsulfuron methyl), triclopyr plus picloram, triclopyr), and one methods of physical control (mowing). Grazing goats involves 15 goats per hectare in infested areas grazing for 12 months. Grazing damages weed physiology and controls its spread (Batten, 1979). Mowing is a mechanical control option that removes the weed foliage. This results in reduced root growth and reduced area of infestation. All possible combinations of these options are considered. Illogical combinations (e.g., combining more than one chemical in a strategy) are excluded. This yields 48 possible control strategies (Table 1).

We have recognised that the choice of control options may depend in part on their non-financial costs. Some of the control options listed in Table 1 can impose

social costs by their potential negative impacts on human health or biodiversity. Chemicals that contain picloram and/or metsulfuron can impose negative impacts to human health if they are sprayed in water catchment area that are used for human consumption. Strategies that include these chemicals are numbers 3-5, 11-16, 21-23, 27-29, 35-40, and 45-47. Therefore the paper includes results that exclude the use of these chemicals in the water catchments. Fragile native vegetation can also potentially be damaged by grazing goats and mowing (Tiver and Andrew 1997). We provide results that also exclude these practices (strategies 7-24 and 31-44) for cases where native vegetation is fragile.

In bio-economic studies of this type, availability of scientific data to select parameter values is often a challenge. In this study, we relied on published research to the greatest extent possible (Table 1)².

Efficacy multipliers of control strategies represent the per cent area that remains infested by blackberry after control. Efficacy multipliers of control strategies ($\zeta(u_t)$) are stochastic and depend on the state of nature $q \in \{1, \dots, 21\}$. The expected efficacy multiplier, $E(\zeta(u_t))$, for those strategies that include only a single treatment option (strategies 2-8 and 25) are obtained from the literature, as presented in Table 1. The expected efficacy multipliers of the strategies that are a combination of more than one control option are calculated from the following formula (from Chalak-Haghighi et al 2008):

---

² As is common in such studies, lack of data meant that we had to rely on expert opinion for estimation of some parameters. In these cases, we took care to ensure that opinions were sought from the most appropriate national experts. Their advice was scrutinised by the researchers for consistency, and reviewed by other experts. In addition, comprehensive sensitivity analysis is conducted, to identify any parameters to which results are particularly sensitive. Through this combination of strategies, we aim to extract the most useful and reliable insights from the available knowledge.

$$E(\zeta(u_t)) = 1 - \prod_{s=1}^S ((1 - Ef_s)) \quad (2)$$

where $E(\zeta(u_t))$ is the expected efficacy multiplier of control strategy, $s = \{1, \dots, S\}$ are control options included in the strategy, and Ef_s is the efficacy multiplier of control option s (i.e., the proportion of weeds removed).

The control cost of chemicals is the summation of chemical costs and the labour costs of spraying. Given the often difficult accessibility of environmental land invaded by blackberry, spraying requires 67 hours of labour at a rate of \$75 hour⁻¹. Thus the labour costs are set at \$5000 ha⁻¹ (Reeves2009). Chemical costs are calculated by multiplying the recommended application rate of each chemical (Anonymous 2006) by its market price in 2009 (Moore and Moore 2009). Goat costs include daily monitoring (\$157ha⁻¹), medicine (\$15 ha⁻¹), fencing (\$2835 ha⁻¹), and capital costs for Boer goats (\$600 ha⁻¹) (Osborne 2009; Moore and Moore 2009).

Table 1 near here

2.3 Simulation model

The spread of blackberry is simulated in a spatially explicit model with a one metre by one metre grid size. The rate of blackberry spread and new infestations are enhanced by higher soil moisture (Moore 2009). Although there is no published literature on the effect of soil moisture on *Rubus anglocandicans*, McDowell and Turner (2002) showed that fruiting and growth of its close relative (*Rubus discolor*) is reduced by moisture deficit. Given that soil moisture is a decreasing function of distance from the river, for the simulation of blackberry spread we divided the area that is susceptible to blackberry infestation into two zones. The first zone is the area within 5 metres of the river and the second zone, which has lower soil moisture, represents the area that is 5-100 metres from the river (Figure 1). Therefore the spread of blackberry is faster in

the first zone (Moore 2009). The area of interest is a riparian area of 330,000 m length by 100 m width. However, as noted below, for reasons of computational tractability we simulate a subset of that area.

There are two ways that a cell may become infested: by spread from a directly neighbouring cell, or longer distance spread (e.g. seed movement by birds or water). It is assumed that the latter process can result in a new infestation in any cell of the model in any year. Moore (2009) used a field experiment to estimate the number and the size of patches due to seed movement caused by animals or water over a block of land along the river. He estimated that there would be 16 new infestations per ha per year, so that 16 grid cells (of 1 m²) out of 10,000 would be infested. Thus the probability of a new infestation in the first zone is 0.0016 per hectare per year. In the second zone, new infestations occur with lower probability due to decreased soil moisture. It was estimated that there would be an average of 0.21 new infestations per ha, giving a probability of 0.000021 per ha per year (Moore 2009).

Figure 1 near here

The model is dynamic, with an annual time step. $t \in T$ indexes time when $T = \{0, 1, 2, 3, \dots, T_{\max}\}$ (3)

where $T_{\max} = 25$. Simulating the spatially explicit spread of blackberry along the entire Gwydir River is not practical due to large computational requirements. Thus, we simulate the spread of blackberry in a 10×100 metre area of land to represent the spread of blackberry along Gwydir River. The representative land consists of 10 columns (parallel to the river) and 100 rows (vertical to the river). L_{ij} represents cells within the landscape where i indexes the rows and j indexes the columns.

$L_{ijt} \in \{0,1\}$ is the state of land unit (i,j) at time t . $L_{ijt} = 1$ if the land unit is infested by blackberry and $L_{ijt} = 0$ if the land unit is not infested.

For initial infestation in year $t = 0$ we have:

$$\begin{cases} L_{ij0} = 1, \text{ if } (RAND) \leq Pr_n \\ L_{ij0} = 0, \text{ otherwise} \end{cases} \quad (4)$$

where Pr_n is the probability that a new infestation occurs in one land unit and $n \in \{1,2\}$ indexes the zones: $n=1$ for the first zone and $n=2$ for the second zone.

$RAND$ is a randomly generated variable with uniform distribution between zero and one. It is used here to implement binary random variables, such as the occurrence of a new infestation. A separate random draw takes place for each cell, each year. Once blackberry is established in a cell, the rate of spread is 2 m yr^{-1} in the first zone ($n = 1$) and 1 m yr^{-1} in the second zone ($n = 2$).

Typically, blackberry does not occupy every square metre of an infested region. To represent this, the probability of a new cell becoming infested at random (Pr_s) depends on the current density of blackberry over the whole modelled region. Current blackberry density is calculated from the following formula:

$$R(L) = \frac{\sum_i^I \sum_j^J L_{ij}}{L} \quad (5)$$

where $R(L)$ represents the proportion of land infested by blackberry. The relationship between the density of blackberry and Pr_s is based on the following 4 points:

- 1) $Pr_s=1$ when there is an infested neighbouring cell in year $t-1$ and if the density of blackberry approaches zero,
- 2) $Pr_s=0$ when the density of blackberry reaches its carrying capacity (i.e. when blackberry infests 75% of the land)

3) $Pr_s=0.9$ when the density of blackberry is 20% and there is an infested neighbouring cell in year $t-1$.

4) $Pr_s=0.3$ when the density of blackberry is 40 % and there is an infested neighbouring cell in year $t-1$ (Moore 2009).

The following logistic function was calibrated to represent these four points.

$$Pr_s = \frac{1}{1 + \exp(-5.5 + 16.18 \cdot R(L))} \quad (6)$$

Thus blackberry invades its new neighbour if

$$RAND \leq Pr_s \quad (7)$$

Figure 2. shows the probability of blackberry invading a new area is a decreasing function of the area currently occupied by blackberry.

Figure 2 near here

Thus in the absence of control and for the first zone:

$$\begin{cases} L_{ijt} = 1, \text{ if } L_{ijt-1} = 1 \text{ or } RAND \leq Pr_{n=1} \text{ or } [RAND \leq Pr_s \text{ and } \sum_{k=i-2}^{i+2} \sum_{l=j-2}^{j+2} L_{klt-1} \geq 1] \\ L_{ijt} = 0, \text{ otherwise} \end{cases} \quad (8)$$

where (k,l) indexes the land units that are within 2 metres of L_{ij} .

and for the second zone:

$$\begin{cases} L_{ijt} = 1, \text{ if } L_{ijt-1} = 1 \text{ or } RAND \leq Pr_{n=2} \text{ or } [RAND \leq Pr_s \text{ and } \sum_{k=i-2}^{i+2} \sum_{l=j-2}^{j+2} L_{klt-1} \geq 1] \\ L_{ijt} = 0, \text{ otherwise} \end{cases} \quad (9)$$

where (y,z) indexes the land units that are within 1 metre of L_{ij} .

Based on these assumptions, the simulation model is implemented in Microsoft Excel and used to generate the transition function for the density of blackberry between year t and year $t+1$ (Figure 3). The stochastic nature of the simulation model is evident from the scatter of data points. An equation is fitted to the modelled data (equation (12)) for use in the optimisation model. A cubic function is used as it provides a good approximation of the shape of the relationship. Parameters are estimated using least squares. As the data exhibit heteroskedasticity, we estimate heteroskedasticity-consistent standard errors, which are reported in parentheses in equation (10).

Figure 3 near here

$$w_{t+1} = (0.945w_t^3 - 1.46w_t^2 + 1.53w_t + 0.023) \quad (10)$$

(0.056)   (0.069)   (0.023)   (0.0020)

$$R^2=0.9973$$

where w_{t+1} is percentage coverage of blackberry in year $t+1$.

The probability that a control strategy will successfully remove blackberry from each cell (L_{ijt}) is represented by its expected efficacy multipliers (see Table 1). Thus, after the application of a control strategy, blackberry will be removed from an infested land unit when:

$$RAND \leq Pr_e \quad (11)$$

where Pr_e is the probability that blackberry is removed by a control strategy (Table 1). Efficacies are obtained from the literature and are translated to probabilities. For example for strategy 16, $Pr_e=0.986$ which means that if this strategy is applied, there is a 98.6% probability of removing blackberry from the land unit. In this case, an infested cell will become uninfested by control if $RAND \leq 0.986$. Note that if a treatment strategy is not applied, its $Pr_e = 0$.

Combining equations 8 and 9 with 11 gives the probability that a land unit is infested by blackberry after control. Thus for the first zone:

$$\begin{cases} L_{ijt} = 1, \text{ if } RAND \geq Pr_e \text{ and } \{L_{ijt-1} = 1 \text{ or } RAND \leq Pr_{n=1} \text{ or } [RAND \leq Pr_s \text{ and } \sum_{k=i-2}^{i+2} \sum_{l=j-2}^{j+2} L_{klt-1} \geq 1]\} \\ L_{ijt} = 0, \text{ otherwise} \end{cases} \quad (12)$$

and for the second zone:

$$\begin{cases} L_{ijt} = 1, \text{ if } RAND \geq Pr_e \text{ and } \{L_{ijt-1} = 1 \text{ or } RAND \leq Pr_{n=2} \text{ or } [RAND \leq Pr_s \text{ and } \sum_{k=i-2}^{i+2} \sum_{l=j-2}^{j+2} L_{klt-1} \geq 1]\} \\ L_{ijt} = 0, \text{ otherwise} \end{cases} \quad (13)$$

Thus, net benefits after control (B_t) are defined as:

$$B_t = lv_t(1 - w_t) - c(u_t) \quad (14)$$

where land value (lv) is the value of land for healthy vegetation in the absence of infestation by the weed, w is the portion of land infested and $c(u_t)$ represents the cost of control strategy “ u ” at time t . The Net Present Value (NPV) obtained from applying each strategy is:

$$NPV = \sum_{t=0}^T \frac{B_t}{(1+\sigma)^t} \quad (15)$$

where B_t is the net benefit obtained from the environment (see equation 1) and σ is the discount rate. NPVs of alternative control strategies are compared and ranked.

2.4 Optimisation model

As explained above, the efficacy multiplier of each control strategy ($\zeta(u_t)$) is stochastic. The expected efficacy multipliers, $E(\zeta(u_t))$, is assumed to be known.

We assume the realisations of strategy efficacy multipliers depend on the state of nature. States of nature are indexed by q . Equation 10 describes the weed dynamics before control and the following equation describes the dynamics of blackberry after control:

$$w_{qt+1} = (0.945w_{qt}^3 - 1.46w_{qt}^2 + 1.53w_{qt} + 0.023) \cdot \zeta_q(u_t) \quad (16)$$

where $\zeta_q(u_t)$ is the realised efficacy multiplier, which represents the percentage of blackberry that remains after control strategy u_t . For example, for strategy 1 (no control) when $\zeta_q(u_t)=1$. This means that for this strategy weed density in year $t+1$ (w_{t+1}) is multiplied by one and will remain unchanged. However, if $\zeta_q(u_t)=0.2$, weed density in year $t+1$ will be weed density in year t multiplied by 0.2 due to control, representing the removal of 80% of the weeds.

Benefits (B_t) depend on the efficacy of the strategy used, which depends on the state of nature, such that efficacy has a lognormal distribution. Efficacy is assumed to have a standard deviation of 5% (Reeves 2009), and its distribution is truncated at plus 10 per cent and minus 15 per cent relative to the expected efficacy ($E(\zeta(u_t))$) and scaled to provide a total probability of 1.0. The distribution is approximated as a

discrete distribution with 21^3 states of nature. Expected efficacies are provided in Table 1. As the number of combinations of control strategies is large, finding the optimal strategy using the simulation model can be time consuming. To solve this problem, an optimisation model has been developed. The optimisation model finds a sequence of control strategies (u_t) that maximises the expected NPV (ENPV_t). The total number of integrated strategies (IS) is ts where $1 \leq u_t \leq ts$, so $IS = \{1, \dots, ts\}$. IS is divided into two categories: (a) $IS_r = \{1, \dots, ts_r\}$, which represents integrated weed strategies that include rust, with ts_r representing the total number of strategies that include rust, and (b) $IS_{nor} = \{ts_r+1, \dots, ts\}$, which represents strategies that do not include rust. If, in year t , a strategy is chosen from IS_r , in subsequent years only strategies in category IS_{nor} will be chosen. The optimisation model follows:

$$EV_t(w_t) = \underset{u_t}{Max} \left\{ \sum_q pr_q \times (B_t(w_{qt}, u_t) + \delta V_{t+1}(w_{qt+1})) \right\} \quad (17)$$

Subject to:

$$w_{qt+1} = (0.945w_{qt}^3 - 1.46w_{qt}^2 + 1.53w_{qt} + 0.023) \cdot \zeta_q(u_t) \quad (18)$$

$$u_t \in IS \quad \vee \quad u_{t-(1t-1)} \notin IS_r \quad (19)$$

$$u_t \in IS_{nor} \quad \vee \quad u_{t-(1t-1)} \in IS_r \quad (20)$$

where δ is the discount factor and pr_q is the probability that state of nature q occurs.

The benefits in year t depend on the weed density in year t and the control strategy adopted (u_t). Future net benefits, however, are affected by the future weed density.

The dynamic programming model is solved using backward induction by MATLAB for a planning horizon of 25 years.

---

³ Sensitivity analysis showed that the results remain unchanged if the number of states of nature increases beyond 21.

We conclude this discussion of methods by acknowledging some limitations of the study. We have endeavoured to include biologically realistic relationships and relevant control strategies in the study. Nevertheless, a number of limitations remain. The key limitation arises from lack of biological data and relationships. We have described our model as being relevant to southern Australia. In reality, physical conditions vary greatly across southern Australia, but we lack the information to adjust the model to make it highly tuned to local conditions. We have also simplified the analysis by focusing on a single weed. In some locations there may be multiple weeds present, with interactions between the results of different control methods.

3. Results and discussion

We firstly present the weed density and benefits obtained from a selected set of control strategies. We compare the no-action strategy with strategies that consist of either a single non-chemical treatment or are a combination of chemical and non-chemical controls. For this, the simulation model is used. Secondly we use the optimisation model to identify the optimal integrated control strategy and perform a sensitivity analysis to show the effect of varying parameters on the optimal strategy.

The two models have different strengths: the stochastic simulation model is spatially explicit, and accounts for stochastic elements such as introduction of new infestations and the probability of blackberry being removed by each control strategy. The stochastic simulation model calculates the dynamics of blackberry density – the density in year $t+1$ as a function of density in year t . Because the resulting relationship is not highly stochastic, it is approximated in the optimisation model as a deterministic relationship. However, the optimisation model does take into account the stochasticity of control efficacies, which has a greater variance than does the dynamic density relationship. The use of two models allows us draw on the strengths

of both models, and to verify the accuracy of each model, through the comparison of results for equivalent scenarios.

Results show that it is optimal to introduce rust (*Phragmidium violaceum*) as a biological agent. In the presence of rust, strategy 47 is optimal. Sensitivity analysis⁴ shows that, if chemical efficacy decreases by 20%, the optimal strategy is still 47 and, if chemical efficacy increases by 20%, strategy 27 becomes optimal. However, we note that including rust only slightly increases ENPV, while excluding rust does not affect the optimal choice of other control options. This reflects the low level of efficacy assumed for this treatment (less than 5 per cent kill, based on Mahr and Bruzzese (1998)). We also note that there is always a risk associated with the introduction of biological control agents. Some such agents introduced for pest control can feed on alternative host plants (i.e. plants other than the target pest) and may have important adverse consequences (Henneman and Memmott, 2001; Symondson et al 2002; Rand et al 2006; Wirth et al 2007). Given the low economic benefits of introducing rust and its potential negative consequences, in the remainder of this paper we focus on strategies 1-24 which do not include rust.

3.1 Effects of selected control options on benefits and weed density

Each control strategy results in a different weed density and generates different benefits and costs. Here we first compare the weed density and net benefits for selected strategies. Figure 4 shows blackberry density for four strategies. These strategies are selected for illustrative purposes and are not necessarily optimal. They include: strategy 1 (no control), strategy 8 (mowing) which has a relatively low efficacy, strategy 19 (goat grazing and mowing) which is a combination of two non-chemical treatments and strategy 23 (combination of triclopyr plus picloram, goat

---

⁴ Results not presented in the paper show that the selection of strategies is generally robust in response to changes in the discount rate.

grazing and mowing) which is a combination of chemical and non-chemical treatments.

Figure 4 near here

In the absence of control, at the beginning of the time horizon, the density of weed rapidly increases. As the weed density increases, weed spread reduces due to increasing occupation of the available space. Strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing) is optimal and has a high efficacy (see Table 1) which keeps the weed density at a very low level (it is, in fact, the optimal strategy overall). Strategy 19 has the next most effective weed control, followed by strategy 8. They result in higher blackberry densities than does Strategy 23.

Figure 5 presents the undiscounted year-by-year net benefits for the strategies shown in Figure 4. These results are net benefits for each year. Net benefits in later years reflect, to some degree, the degree of weed control in earlier years. Thus, net benefits in a single year do not necessarily reflect the full benefits of weed control in that year. As this figure shows, for most years, strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing) is preferred over other control options. Strategy 23, however, is expensive. Thus, at the beginning of the time horizon where the weed density is very low, the annual net benefit of “no control” is higher than that for strategy 23. But as the weed density increases, the benefit obtained from maintaining the weeds at a low density exceeds the control cost and strategy 23 become relatively more attractive.

Figure 5 near here

Strategies 8 (mowing) and 19 (goat grazing and mowing) are less costly than strategy 23, but have lower levels of weed kill (see Table 1). In this example, the loss of weed kill outweighs the benefits of lower cost, so strategy 23 is preferred. On the

other hand, strategy 19 (goat grazing and mowing) results in a lower weed density than does strategy 8 (Figure 4), but the control cost of strategy 19 is so high that it has lower net benefits overall (Figure 5). Indeed, it has lower net benefits than the “no control” option in all years. This latter result is sensitive to the non-market value ascribed to the protection of the river bank (obtained from Morrison and Bennet (2004)). If the value increases by 5%, the benefit of applying strategy 19 exceeds the benefits of strategy 1 (no control).

3.2 Optimal strategies and sensitivity analysis

Here we present results of the dynamic optimisation model. This model provides the optimal decision options for each year depending on the current weed density.

An extensive sensitivity analysis is performed to show how changes in the land value and weed density affect the optimal strategy (Figure 6). All other variables are at their base-case values (from Table 1). In the judgement of the authors, uncertainty about the land value used is high. Sensitivity analysis (Pannell 1997) is conducted in order to explore the consequences of this uncertainty (see Figure 6). Each point in the graphed space of this figure represents a combination of land value and initial weed density. For combinations that lie below/left of the threshold line, strategy 1 (no control) is optimal, while for combinations above/right of the threshold line, strategy 23⁵ (combination of triclopyr plus picloram, goat grazing and mowing) is optimal. The figure shows that the model results are robust in the face of large changes: for the great majority of land value/weed density combinations, strategy 23 remains optimal. Exceptions are when initial infestation and/or total land value is very low, when it becomes optimal to switch to no control (strategy 1).

Figure 6 near here

---

⁵ Note that strategy 23 is optimal if there are no restrictions in the use of chemicals and the introduction of rust is excluded.

Table 2 shows results for sensitivity analysis investigating 20% increases⁶ or decreases in efficacy for chemicals, goat grazing and mowing. In order to compare the impacts of varying the efficacy of the control treatments on ENPV, strategies 3 (glyphosate plus metsulfuron), 5 (triclopyr plus picloram), 8 (mowing), 19 (combination of goat grazing and mowing), 21 (combination of glyphosate plus metsulfuron, goat grazing and mowing) and 23 (combination of triclopyr plus picloram, grazing goat and mowing) were selected for simulation. These control strategies are not necessary optimal and are selected for comparison and illustration. For a list of ENPVs for all control strategies see Table A.1. Rows in Table 2 represent scenarios, with variations in model parameters. The optimal strategy in each scenario is the one with the highest ENPV, which is highlighted in grey. For example, strategy 23 is optimal for scenarios 1, 3, 5, 6 and 7 while strategy 3 is optimal for scenario 2. The fact that strategy 23 is optimal for most scenarios indicates that the results (in terms of the optimal strategies) are relatively insensitive to changes in the treatment efficacies. This is readily explicable: when the efficacy of chemicals decreases by 20%, the efficacies of strategies that include chemicals (e.g. strategies 3, 5, 21 and 23) decreases by similar amounts. The efficacy of non-chemical strategies (e.g. strategies 8 and 19) are lower than the efficacy of strategy 23 even when the efficacy of chemicals decreases by 20%. Therefore strategy 23 remains optimal. However, strategy 3 becomes optimal if the efficacy of strategy 23 is decreased by 20% while the efficacy of other strategies remains unchanged.

Table 2 near here

---

⁶ Note that the maximum efficacy is 100 per cent blackberry removal. For strategies with high efficacies, upward variation in efficacy runs the risk of generating levels greater than 100%. In any such cases, the efficacy is truncated at 100%. (e.g. for a strategy with 85 percent efficacy, a scenario involving a 20 percent increase in efficacy would result in 100 percent efficacy).

If the efficacy of chemicals increases by up to 20 percent (scenario 1 in Table 2), strategy 3 (application of glyphosate plus metsulfuron) replaces strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing) as the optimum. In other words, as a result of greater herbicide efficacy, an integrated strategy combining herbicides and physical control is replaced by a herbicide-only strategy. This is because, in this sensitivity scenario, all chemicals have efficacy levels of 100%, so the optimum becomes the cheapest chemical strategy, Strategy 3.

Goat grazing and mowing can be more environmentally friendly control options so it is interesting to see whether an increase in their efficacy can make them cost-effective options for blackberry control. Results show that when the efficacy of goat grazing and mowing increase or decrease by 20 percent (scenarios 3-6 in Table 2), the ENPVs of the strategies that include goat grazing and mowing (strategies 8, 19, 21 and 23) increase or decrease accordingly. However, strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing) remains optimal, due to its higher level of efficacy. However, goat grazing becomes optimal if the efficacy of goat grazing increases from 45% to at least 99%.

For the strategies that include more than one control option, the change in the efficacy of one control option will be moderated to some extent by other control options. Thus, when a strategy includes more than one control option, ENPV is less sensitive to change in the efficacy of individual control treatments as compared with single-treatment strategies. This reflects one of advantages of combined control strategies versus single-treatment strategies. Table 2 illustrates the impacts of varying individual efficacy parameters on the ENPV. The results reinforce that the optimal strategy is sensitive to the efficacy of herbicides, but not to similar percentage

changes in the efficacy of physical control methods. At reduced chemical efficacy (-20%), the optimal strategy is number 23 (combination of triclopyr plus picloram, grazing goat and mowing). At increased efficacy (+20%⁷), it is number 3 (glyphosate plus metsulfuron). At the base-case efficacy it is 23. These results apply, regardless of variations in goat efficacy or mowing efficacy within 20 per cent of the base case.

We extend the sensitivity analysis by investigating the impact of varying the cost of chemicals, goat grazing and mowing on ENPV, for the list of selected strategies (i.e. strategies 3, 5, 8, 19, 21 and 23). Results show that strategy 23 is optimal for all scenarios in Table 3 and the model is insensitive to changes in the control costs.

Table 3 near here

Now we investigate the sensitivity of the optimal ENPV to 20% variations in the efficacy of grazing goats, mowing and chemicals (Table 4). A decrease in the efficacy of chemicals has a larger impact on the ENPV than does an increase in chemical efficacy. This reflects that the herbicide-dominant strategies already provide a high level of weed control, so increases in weed kill are of limited value. Indeed, the results show that a 20 per cent increase⁸ in herbicide efficacy increases ENPV by less than 0.1%. Thus, any expenditure on this improvement of efficacy could be justified only at very low cost. Similarly, upward variations in the efficacy of grazing goats and mowing have smaller impacts on the optimal ENPV than do downward variations. If the efficacy of grazing goats and mowing increases by 20%, ENPV improves by less than 2%, and if the efficacy of grazing goats and mowing decreases by 20% ENPV decreases by up to 6%.

Table 4 near here

---

⁷ See footnote 1.

⁸ See footnote 1.

3.3 Restricted treatment options

As explained earlier, chemicals such as metsulfuron and picloram cannot be used in water catchment area that are sources for human consumption (PCS88 2007; Reeves 2009). Furthermore, there may be areas where grazing goats and mowing cannot be applied due to negative impacts on native vegetation. In this section we first examine a case where metsulfuron and picloram cannot be used but where grazing goats and mowing are acceptable. Sensitivity analysis (not shown in a table) shows that when the efficacy of chemicals is at base case or 20 per cent lower, the new optimum is strategy 24, a combination of triclopyr (an acceptable herbicide), grazing goats and mowing. When efficacy of chemicals increase by 20 per cent⁹, the optimal strategy switches to number 6 (application of triclopyr alone). As before, the optimal strategy is not sensitive to the efficacy of physical control methods. The results show that increases in the efficacy increases ENPV by less than 0.1%. Thus, expenditure on the improvement of efficacy can be justified only at sufficiently low costs.

We also examine the most restricted scenario, where the environmental manager is unable to use the two physical control methods (grazing goats and mowing) or the high-risk chemicals. In this case the optimal management strategy is number 6 (application of triclopyr) and remains so even if chemical efficacy is varied up or down by 20 per cent.

4. Conclusions

This paper employs a stochastic dynamic simulation model and a dynamic optimisation model to find the most cost-effective integrated control options for blackberry in riparian areas in Australia. To do this, 48 combinations of control

---

⁹ See footnote 1.

treatments have been evaluated to determine the optimal integrated strategies in different scenarios. The simulation model provides weed dynamics and calculates ENPV for each strategy while the optimisation model provides the optimal management decision options for the problem in each year depending on the current weed density. The results of the two models are fully consistent.

The results indicate that, while an integrated strategy combining chemical and non-chemical control methods may be optimal in certain circumstances (e.g. Pannell et al 2004; Chalak-Haghighi et al 2008), it is not necessarily superior to a chemical-dominant strategy in all cases. Thus, policy makers who currently rely solely on chemical weed control should carefully assess the costs and benefits of including a non-chemical control option to assess whether its marginal cost exceeds its marginal benefit.

For a scenario where all technically feasible control methods are allowable, a combination of herbicides and two physical control methods (mowing and goat grazing) is optimal in the base-case scenario. This shows that, for this case study, where non-chemical methods are available, integrated control strategies are superior to the application of a single chemical. If chemical efficacy is 20 per cent greater than in the base-case, the optimal strategy involves chemicals only. However, if chemical efficacy decreases by 20 per cent, the optimal strategy remains unchanged.

Weed control strategies need to be sensitive to their impacts on natural environment, so we examined the impact of restricting the set of control options to exclude options with relatively high environmental risks. Such restrictions can play a major role in determining the optimal strategy, in this case resulting in a preference for strategies involving treatments that would not otherwise be optimal.

The results indicate that biological methods (i.e. grazing goats and rust) can be optimal to control blackberry despite their relatively low efficacy and the greater uncertainty about their effectiveness. However, we do not recommend using rust because, on one hand, its estimated benefits are small, and on the other hand, the use of biological agents such as rust involves potential risks. A strategy of using grazing goats, on the other hand, is a more favourable treatment than rust due to their higher level of weed control efficacy. Given the cost-effectiveness of grazing goats for blackberry control, we encourage policy makers to consider grazing animals as a potentially cost-effective mean for the control of weed in environment. We note that application of grazing goats with other control options has been recommended in the literature. For example, grazing goats has been found optimal to control leafy spurge (*Euphorbia esula*) which occurred across the Great Plains and Mountain West from Canada to New Mexico (Lym 2005). In considering this strategy, policy makers should assess its cost-effectiveness and any externalities generated. This study not only takes into account the social benefits of weed control but also considers social costs associated with the use of some chemicals. For example, we have introduced scenarios where the use of some chemicals is restricted in the water catchment or where grazing goats and mowing damage native vegetation. Thus policy makers need to be aware of the tradeoffs between choosing more effective control options that may impose environmental or health risks versus less effective control strategies that are safer for the environment and human health.

References

- Amor, R. L. and R.V. Harris. 1981.** Effects of mowing and spraying of 2,4,5-T on blackberry (*Rubus fruticosus* agg.) and pasture species. *Australian Journal of Experimental Agriculture and Animal Husbandry* 21: 614-617.
- Anonymous. 2006.** Weedy blackberry and raspberry species in Western Australia and strategies for their management. <http://www.csiro.au/Outcomes/Safeguarding-Australia/Blackberry-Management-WA.aspx> (accessed May 7, 2009).
- Apan, A., N. Wells, K. Readerdon-Smith, L. Richardson, K. McDougall and B. Basner. 2008.** Predictive mapping of blackberry in the Condamine catchment using logistic regression and spatial analysis. Queensland Spatial Conference, Gold Coast.
- Barreto, R. W. 2009.** Latin American weed biological control science at the crossroads, in Julien, M. H., R. Sforza, and M. C. Bon (eds.), *Proceeding of the XII International Symposium on Biological Control of Weeds*, pp. 109-112.
- Batten, G. J. 1979.** Controlling scrub weeds with goats. *New Zealand Journal of Agriculture* 139: 31-32.
- Bergmann, A., S. Colombo, and N. Hanley. 2008.** Rural versus urban preferences for renewable energy developments. *Ecological Economics* 65, 616–625.
- Buckley, Y. M., M. Rees, Q. Paynter and M. Lonsdale. 2004.** Modelling integrated weed management of an invasive shrub in tropical Australia. *Journal of Applied Ecology* 41: 547-560.
- Byrnes, B., C. Jones, S. Goodman. 1999.** Contingent valuation and real economic commitments: evidence from electric utility green pricing programmes. *Journal of Environmental Planning and Management* 42, 149–166.

- Cacho, O. J., R. M. Wise, S. M. Hester and J. A. Sinden. 2008.** Bioeconomic modeling for control of weeds in natural environments. *Ecological Economics* 65: 559-568.
- Cacho, O. J., S. Hester and D. Spring. 2007.** Applying search theory to determine the feasibility of eradicating an invasive population in natural environment. *Australian Journal of Agricultural Resource and Economics* 51: 425-443.
- Chalak, M., A. Ruijs and E. C. van Ierland. 2009.** On the economics of controlling an invasive plant: a stochastic analysis of a biological control agent. *International Journal of Environmental Technology and Management* 11: 187-206.
- Chalak-Haghighi, M., E. C. van Ierland, G. W. Bourdôt and D. Leathwick. 2008.** Management strategies for an invasive weed: a dynamic programming approach for Californian thistle in New Zealand. *New Zealand Journal of Agricultural Research* 51 (4): 409-424.
- Chock, M., K. Burnett, and L. Donna. 2010.** An Economic Assessment of Biological Control for *Miconia calvescens* in Hawaii. University of Hawai'i Economic Research Organization (UHERO) University of Hawaii-Manoa. Manoa, Hawaii. 34p.
- Cogliastro, A., K. Benjamin and A. Bouchard. 2006.** Effects of full and partial clearing, with and without herbicide, on weed cover, light availability, and establishment success of white ash in shrub communities of abandoned pastureland in South Western Quebec, Canada. *New Forests* 32: 197–210.
- Derera, J., G. P. Denash and K. V. Pixley. 2000.** Resistance of maize to the maize weevil: II. non-preference. *African Crop Science Journal* 9: 441-450.

- Ehler, L. E. 1998.** Invasion biology and biological control. *Biological Control* 13: 127-133.
- Eiswerth, M. E. and G. C. van Kooten. 2007.** Dynamic programming and learning models for management of a nonnative species. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 55(4): 485-498.
- Epanchin-Niell, R. S. and A. Hastings. 2010.** Controlling established invaders: integrating economics and spread dynamics to determine optimal management. *Ecology Letter* 13(4): 528-541.
- Ethier, R. G., G. L. Poe, W. D. Schulze, and J. Clark. 2000.** A comparison of hypothetical phone and mail contingent valuation responses for green-pricing electricity programs. *Land Economics* 76, 54–67.
- Fernandez, L. 2011.** Economic Incentives to Prevent Aquatic Invasive Species in Wetlands. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 59(2): 281-293.
- Fried, G., E. Kazakou and S. Gaba. 2012.** Trajectories of weed communities explained by traits associated with species' response to management practices. *Agriculture, Ecosystems & Environment* 158: 147-155.
- Gammie N. 2009.** Biologist and expert on salinity in the Gwydir River, Department of Primary Industry. Personal phone communication, April. **Giljohann, K. M., C. E. Hauser, N. S. Williams, and J. L. Moore. 2011.** Optimizing invasive species control across space: willow invasion management in the Australian Alps. *Journal of Applied Ecology* 48(5): 1286-1294.
- Grimsrud, K. M., J. M. Chermak, J. Hasen, J. A. Thacher and K. Krause. 2008.** A two-agent dynamic model with an invasive weed diffusion externality: An

- application to Yellow Starthistle (*Centaurea solstitialis* L.) in New Mexico. *Journal of Environmental Management* 89 (4): 322-335.
- Hart, S. P. 2001.** Recent perspectives in using goats for vegetation management in the USA. *Journal of Dairy Science* 84: 170-176.
- Henneman, M. L., and J. Memmott. 2001.** Infiltration of a Hawaiian community by introduced biological control agent. *Science* 293: 1314–1316.
- Hester S. M., S. J. Brooks, O. J. Cacho and F. D. Panetta. 2010.** Applying a simulation model to the management of an infestation of *Miconia* (*Miconia calvescens*) in the wet tropics of Australia. *Weed Research* 50(3): 269-279.
- James, R. and M. Lockwood. 1998.** Economics of blackberries, current data and rapid valuation techniques. *Plant Protection Quarterly* 13(4): 175–179.
- Jayasuriya, R. T., R. E. Jones, and R. van de Ven. 2011.** A bioeconomic model for determining the optimal response strategies for a new weed incursion. *Journal of Bioeconomics*: 13(1), 45-72.
- Kaiser, B., K. Burnett and J. Roumasset. 2010.** *Control of invasive species: lessons from Miconia in Hawaii*. University of Hawai'i Economic Research Organization (UHRO). Manoa, Hawaii. 25p.
- Kennedy, J. O. S. 1987.** The economics of weed control. *Plant Protection Quarterly* 2: 118-123.
- Llewellyn, R. S., R. K. Lindner, D. J. Pannell, and S. P. Powles. 2007.** Herbicide resistance and the adoption of integrated weed management. *Agricultural Economics* 36: 123-130.
- Longo, A., A. Markandya, and M. Petrucci. 2008.** The internalization of externalities in the production of electricity: willingness to pay for the attributes of a policy for renewable energy. *Ecological Economics* 67, 140–152.

- Lym, R. G. 2005.** Integration of biological control agents with other weed management technologies: Successes from the leafy spurge (*Euphorbia esula*) IPM program. *Biological Control* 35(3): 366-375.
- Mahr, F. A. and E. Bruzzese. 1998.** The effect of *Phragmidium violaceum* (Shultz) winter (Uredinales) on *Rubus fruticosus* L. agg. in southern Victoria. *Plant Protection Quarterly* 13: 182-185.
- Marczak, L. B., T. Sakamaki, S. L. Turvey, L. Deguise, S. L. R. Wood, and J. S. Richardson. 2010.** Are forested buffers an effective conservation strategy for riparian fauna? An assessment using meta-analysis. *Ecological Application* 20: 126–134.
- McConnachie, A. J., M. P. de Wit, M. P. Hill and M. J. Byrne. 2003.** Economic evaluation of the successful biological *Azolla filiculoides* in South Africa. *Biological Control* 28: 25-33.
- McDowell S. C. L and D. P. Turner. 2002.** Reproductive effort in invasive and noninvasive *Rubus*. *Oecologia* 133: 102–111
- Moore, J. H. 2009.** Department of Agriculture, Weed Science. Personal e-mail and phone communication, May.
- Moore, C. B. and J. H. Moore. 2009.** HerbiGuide – The pesticide expert on a disk. (HerbiGuide, Box 44, Albany, Western Australia, 6331) www.herbiguide.com.au (accessed may 7, 2013) .
- Morrison, M. and J. Bennett. 2004.** Valuing New South Wales rivers for use in benefit transfer. *The Australian Journal of Agricultural and Resource Economics* 48: 591-611.

- Odom, D. I. S., O. J., Cacho, J. A. Sinden and G. R. Griffith. 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.
- Osborne H. 2009.** Contractor for weed control using grazing goats. Personal phone communication, May.
- Pannell, D. J. 1997.** Sensitivity analysis of normative economic models: Theoretical framework and practical strategies. *Agricultural Economics* 16(2): 139-152.
- Pannell, D. J., V. Stewart, A. Bennett, M. Monjardino, C. Schmidt and S. B. Powles. 2004.** RIM: A Bioeconomic Model for Integrated Weed Management of *Lolium rigidum* in Western Australia. *Agricultural Systems* 79: 305-325.
- Pardo, G., M. Riravololona, and N. M. Munier-Jolian. 2010.** Using a farming system model to evaluate cropping system prototype: Are labour constraints and economic performances hampering the adoption of Integrated Weed Management? *European Journal of Agronomy* 33: 24-32.
- Pemberton, R. W. 2000.** Predictable risk to native plants in weed biological control. *Oecologia* 125: 489-494.
- Pritchard, G. H. 1990.** Control of rust-infected blackberry with herbicides in Victoria. *Proceeding of the 9th Australian Weed Conference* 6-10.
- Quinn, J. M. 1997.** Land use effects on habitat, water quality, periphyton, and benthic invertebrates in Waikato, New Zealand, hill-country streams. *New Zealand Journal of Marine and Freshwater Research* 31: 579-597.
- Rand, T. A., J. M. Tylianakis, and T. Tscharntke. 2006.** Spillover edge effects: the dispersal of agriculturally subsidized insect natural enemies into adjacent natural habitats. *Ecology Letters* 9: 603-614.

- Reeves A. 2009.** Expert in weed control, Department of Agriculture and Food. Personal e-mail and phone communications, May.
- Sheppard, A. W., R. Hill, R. A. DeClerck-Floate, A. McClay, T. Olckers, Jr. P. C. Quimby and H. G. Zimmermann. 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: 91-108.
- Sinden, J., P. O. Downey, S. M. Hester, and O. Cacho. 2008.** Economic evaluation of the management of bitou bush (*Chrysanthemoides monilifera* subsp. *rotundata* (DC.) T. Norl.) to conserve native plant communities in New South Wales. *Plant Protection Quarterly* 23(1): 34.
- Sy, M., K. Keenleyside, K. Adare, B. Reader, M. Plante, and P. Deering. 2009.** Protecting native biodiversity from high-impact invasive species through the protected areas of Parks Canada. *Biodiversity* 10: 51-55.
- Symondson, W. O. C., K. D. Sunderland, and M. H. Greenstone. 2002.** Can generalist predators be effective biocontrol agents? *Annual Review of Entomology* 47: 561-594.
- Taylor, C. R. and O. R. Burt. 1984.** Near-optimal management strategies for controlling wild oats in spring wheat. *American Journal of Agricultural Economics* 66: 50-60.
- Thomas, M. B. and A. J. Willis. 1998.** Biocontrol-risky but necessary? *Trends in Ecology and Evolution* 13: 325-329.
- Tiver, F., and M. H. Andrew. 1997.** Relative effects of herbivory with sheep, rabbits, goats and kangaroos on recruitment and regeneration of shrubs and trees in eastern South Australia. *Journal of Applied Ecology* 34: 903-914.

- Tyser, R. W. and C. H. Key. 1988.** Spotted knapweed in a natural area fescue grassland: an ecological assessment. *Northwest Science* 62, 151-160.
- Vere, D. T. and J. J. Dellow. 1984.** Estimating the costs of blackberry in Central Western New South Wales. Proceedings of the 7th Australian Weeds Conference, Perth Australia.
- Vere, D. T., R. E. Jones and G. Saunders. 2004.** The economic benefits of rabbit control in Australian temperate pastures by the introduction of rabbit haemorrhagic disease. *Agricultural Economics* 30: 143-155
- Weeds of National Significance 2009.** Weeds of National Significance Strategies, Resources and Comments <http://www.weeds.org.au/WoNS/> (accessed May 12, 2009).
- Wirth, R., S. T. Meyer, I. R. Leal, and M. Tabarelli. 2007.** Plant–herbivore interactions at the forest edge. In *Progress in Botany* by U. Lüttge, W. Beyschlag, and J. Murata, pp. 423–448. Springer-verlag Berlin Heidelberg.
- Wu, J. 2001.** Optimal weed control under static and dynamic decision rules. *Agricultural Economics* 25: 119-130.

Table 1. Costs and efficacies of strategies to control blackberry. Control options are: Rust (R.), Gly. (glyphosate), Gly. + Met. (glyphosate plus metsulfuron), Met. Met. (metsulfuron methyl), Tricl.(triclopyr), Tric. + pic. (triclopyr plus picloram), goats and mowing. EE represents the expected efficacy multiplier $E(\zeta(u_t))$ and Pr_e is the probability that blackberry is removed.

Strategies	Control options	EE	Pr_e	Costs (\$ ha ⁻¹)	References
1	None	1	0	0	
2	Gly.	0.2	0.8	5100	Anonymous (2006)
3	Gly.+Met.	0.05	0.95	5095	Anonymous (2006)
4	Met.Met.	0.25	0.75	5040	Anonymous (2006)
5	Tric.+ pic.	0.03	0.97	5400	Anonymous (2006)
6	Tric.	0.08	0.92	5200	Pritchard (1990),
7	Goats	0.55	0.45	3607	Batten (1979),
8	Mowing	0.48	0.52	500	Amor and Harris (1981)
9	Gly. & Goats	0.11	0.89	8707	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
10	Gly. & Mowing	0.096	0.904	5600	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
11	Gly. + Met. & Goats	0.028	0.972	8702	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
12	Gly. + Met. & Mowing	0.024	0.976	5595	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
13	Met. Met. & Goats	0.138	0.862	8647	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
14	Met. Met. & Mowing	0.12	0.88	5540	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
15	Tric. + pic. & goats	0.017	0.983	9007	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
16	Tric. + pic. & Mowing	0.014	0.986	5900	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
17	Tric. & goats	0.044	0.956	8807	Anonymous (2006); Pritchard (1990); Batten (1979); Chalak-Haghighi et al. (2008)
18	Tric. & Mowing	0.038	0.962	5700	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
19	Goats & Mowing	0.264	0.736	4170	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
20	Gly. & Goats & Mowing	0.053	0.947	9207	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
21	Gly. + Met. & Goats & Mowing	0.013	0.987	9202	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
22	Met. Met. Goats & Mowing	0.066	0.934	9147	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
23	Tric. + pic. & Goats & Mowing	0.008	0.992	9507	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
24	Tric. & Goats & Mowing	0.021	0.979	9307	Anonymous (2006); Pritchard (1990); Amor and Harris (1981); Chalak-Haghighi et al. (2008)

0
1
2
3
4
5
6
7

Table 1. (*continued*)

Strategies	Control options	EE	Pr_e	Costs (\$ ha ⁻¹)	References
25	R.	0.957	0.043	1	Mahr and Bruzzese (1998)
26	R. & Gly.	0.191	0.809	5101	Anonymous (2006); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
27	R. & Gly. + Met.	0.048	0.952	5096	Anonymous (2006); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
28	R. & Met. Met.	0.239	0.761	5041	Anonymous (2006); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
29	R. & Tric. + pic	0.029	0.971	5401	Anonymous (2006); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
30	R. & Tric.	0.077	0.923	5201	Pritchard (1990); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
31	R. & Goats	0.526	0.474	3608	Batten (1979); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
32	R. & Mowing	0.459	0.541	501	Amor and Harris (1981); Chalak-Haghighi et al. (2008); Mahr and Bruzzese (1998)
33	R. & Gly. & Goats	0.105	0.895	8708	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
34	R. & Gly. & Mowing	0.092	0.908	5601	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
35	R. & Gly. + Met. & Goats	0.026	0.974	8703	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
36	R. & Gly. + Met. & Mowing	0.023	0.977	5596	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
37	R. & Met. Met. & Goats	0.132	0.868	8648	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
38	R. & Met. Met. & Mowing	0.115	0.885	5541	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
39	R. & Tric. + pic & goats	0.016	0.984	9008	Anonymous (2006); Batten (1979); Chalak-Haghighi et al. (2008)
40	R. & Tric. + pic & Mowing	0.014	0.986	5901	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
41	R. & Tric. & goats	0.042	0.958	8808	Anonymous (2006); Pritchard (1990); Batten (1979); Chalak-Haghighi et al. (2008)
42	R. & Tric. & Mowing	0.037	0.963	5701	Anonymous (2006); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
43	R. & Goats & Mowing	0.253	0.747	4108	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
44	R. & Gly. & Goats & Mowing	0.051	0.949	9208	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
45	R. & Gly.+Met. & Goats & Mowing	0.013	0.987	9203	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
46	R. & Met. Met. Goats & Mowing	0.063	0.937	9148	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
47	R. & Tric. + pic & Goats & Mowing	0.008	0.992	9508	Anonymous (2006); Batten (1979); Amor and Harris (1981); Chalak-Haghighi et al. (2008)
48	R. & Tric. & Goats & Mowing	0.020	0.98	9308	Anonymous (2006); Pritchard (1990); Amor and Harris (1981); Chalak-Haghighi et al. (2008)

10

Table 2. Expected NPV (\$ ha⁻¹) of different control strategies for alternative efficacies of chemicals, mowing and goat grazing. The expected benefits of the optimal strategies are presented in gray.

Scenarios	Efficacy	Strategy					
		3	5	8	19	21	23
1	Base case	24,457	24,480	19,236	16,939	24,549	24,559
2	Chemicals + 20%	24,657	24,655	19,236	16,939	24,618	24,613
3	Chemicals -20%	16,773	17,417	19,236	16,939	24,028	24,099
4	Goat control +20%	24,457	24,580	19,236	18,595	24,587	24,600
5	Goat Control - 20%	24,457	24,580	19,236	15,441	24,540	24,595
6	Mowing +20%	24,457	24,580	20,326	19,171	24,591	24,600
7	Mowing - 20%	24,457	24,580	17,984	15,122	24,539	24,550

11 Strategy 3: glyphosate plus metsulfuron, Strategy 5: triclopyr plus picloram, Strategy 8: mowing, strategy 19: combination of goat grazing
 12 and mowing, strategy 21: combination of glyphosate plus metsulfuron, goat grazing and mowing, strategy 23: combination of triclopyr
 13 plus picloram, goat grazing and mowing,.

14
15
16

Table 3. Expected NPV (\$ ha ⁻¹) for alternative efficacies when there is no restriction to the use of control options.				
Goat efficacy	Mowing efficacy	Chemicals		
		-20%	Base case	Up to +20%
Base case	Base case	24,099	24,559	24,657
Base case	+20%	24,333	24,600	24,657
Base case	-20%	23,767	24,550	24,657
+20%	Base case	24,325	24,600	24,657
+20%	+20%	24,433	24,606	24,657
+20%	-20%	24,095	24,594	24,657
-20%	Base case	23,845	24,595	24,657
-20%	+20%	24,230	24,599	24,657
-20%	-20%	23,127	24,586	24,657

17
18
19
20
21
22

23

Table 4. Expected NPV (\$ ha ⁻¹) for alternative efficacies where metsulfuron and picloram cannot be used but where grazing goats and mowing are acceptable				
Goat efficacy	Mowing efficacy	Chemicals		
		-20%	Base case	Up to +20%
Base case	Base case	23,783	24,540	24,649
Base case	+20%	24,232	24,572	24,649
Base case	-20%	23,236	24,526	24,649
+20%	Base case	24,151	24,568	24,649
+20%	+20%	24,374	24,585	24,649
+20%	-20%	23,827	24,552	24,649
-20%	Base case	23,405	24,527	24,649
-20%	+20%	24,061	24,551	24,649
-20%	-20%	22,479	24,505	24,649

24

25

Appendix of supplementary information that presents ENPVs for the 48 strategies.

Table A.1. Expected NPV (\$ ha ⁻¹) for 48 control strategies					
Strategy	ENPV (\$ha ⁻¹)	Strategy	ENPV (\$ha ⁻¹)	Strategy	ENPV (\$ha ⁻¹)
1	17,115	17	24,398	33	21,749
2	18,331	18	24,522	34	23,242
3	24,457	19	16,939	35	24,527
4	16,378	20	24,263	36	24,500
5	24,480	21	24,549	37	19,833
6	23,925	22	23,978	38	22,134
7	10,089	23	24,559	39	24,473
8	19,236	24	24,349	40	24,529
9	21,746	25	17,129	41	24,401
10	23,239	26	18,336	42	24,524
11	24,524	27	24,462	43	16,942
12	24,496	28	16,383	44	24,265
13	19,830	29	24,482	45	24,553
14	22,130	30	23,928	46	23,982
15	24,469	31	10,092	47	24,564
16	24,525	32	19,242	48	24,352

Figure legends

Figure 1 Schematic representation of the riparian area. First zone is land that is within the first 5 metres from the river and the second zone is 5-100 metres from the river.

Figure 2 Relationship between % land infested in year t and the probability that the infestation in year t expands to a neighbouring land unit in year $t+1$.

Figure 3 Transition density of blackberry in year t and $t+1$.

Figure 4 Percentage coverage of blackberry over time for different strategies: no control, strategy 8 (mowing), strategy 19 (goat grazing and mowing), strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing).

Figure 5 Net benefit obtained from the land in year t for different strategies: no control, strategy 8 (mowing), strategy 19 (goat grazing and mowing), strategy 23 (combination of triclopyr plus picloram, goat grazing and mowing).

Figure 6 Optimal strategies for a range of land values and weed densities. When the land value and weed density are relatively high (above the threshold line), the optimal strategy is 16 (combination of triclopyr plus picloram and mowing). When the land value and weed density is below the threshold line, the optimal strategy is 1 (no control).

59

60

61

Figure 1

62

63

Figure 2

70

71 Figure 3

72

73

Figure 4

Figure 5

92

93 Figure 6

94

95