Optimising the control of rangeland woody weeds

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Summary There are very few studies that combine ecological population and economic optimisation models to establish integrated weed management (IWM) policies for woody weeds within rangeland grazing systems. This case study attempts to do so and uses a stochastic dynamic programming (SDP) model to determine the optimal weed management decisions for chinee apple (*Ziziphus mauritiana*) in northern Australian rangelands in order to maximise grazing profits. Model simulations were used to generate a weed management threshold frontier and decision rules, based on weed-free grazing gross margins and the cost of different control methods. The ecological-economic optimising framework presented here can be used for many other long-lived plant species.

Keywords Woody weeds, chinee apple, *Ziziphus mauritiana*, grazing, matrix modelling, stochastic dynamic programming, economic optimisation.

INTRODUCTION

Woody weeds pose significant threats to the $A12.3 billion Australian grazing industry. These weeds reduce stocking rate, increase mustering effort and impede cattle from accessing waterways. Vast areas along the entire eastern coast of Queensland are suitable for the spread of chinee apple. To control woody weeds, managers must consider weed recruitment processes, weed damage to productive pastures, the cost and efficacy of different control methods, as well as livestock returns.

Bioeconomic models combine ecological and economic modelling disciplines. But they can sometimes lack biological realism, by using over-simplified population dynamics. The decision model presented here seeks to overcome this inadequacy whilst maintaining economic robustness. The decision model uses a density dependent population model that retains individual weeds within different life stages based on their physical size, as plant size affects their impact on pasture production, control costs and efficacies. Rangelands weed management is infrequent for several reasons: weed management is undertaken over vast areas; the cost of a single weed treatment is high relative to annual grazing returns; and woody weeds are slow growing, so a single control provides benefits for many years.

MATERIALS AND METHODS

A stage projection matrix model was used to estimate future weed populations and the effect of various weed controls. The temporal transition of the weed population can be represented as:

$$\mathrm{x}_{t+1} = (\mathrm{H}_t\mathrm{x}_t) \circ \Upsilon_t - (\varphi_{u_t} \circ \mathrm{x}_t) \qquad (1)$$

x_t is the population vector for the number of individuals in each life stage, at time t. Υ_t is the stochastic recruitment of seedlings based on rainfall data from Charters Towers in Qld (values are $\Upsilon \geq 0$; $\overline{\Upsilon} = 1$ and are selected by Monte-Carlo sampling), u_t is the control decision, and the mortality rate for each life-cycle stage is represented by an efficacy vector φ for different control actions (u). H_t is a density-dependent stage projection matrix with dimensions n × n; where n is the number of life cycle stages. The three main life cycle stages of woody weeds are seeds, juveniles and adults. Seeds are broken into sub-states, new seeds (*NS*) and seed bank (*SB*). Juvenile (*J*), and adults (*A*) have sub-stages ($J_1, J_2, \ldots, J_m$) and ($A_1, A_2, \ldots, A_q$), based on the time required to reach maturity and plant longevity (Figure 1). For a detailed description of how H_t is derived see Zull *et al*. (2008).

Weed damage to pasture production is modelled with Cousens' (1985) rectangular-hyperbola function:

$$D_t = \frac{\psi\,\mathrm{x}_t}{1 + \dfrac{\psi\,\mathrm{x}_t}{\tau}} \qquad (2)$$

D_t is the proportion of pasture-production lost at time t due to weeds, ψ is a damage vector index for the average amount of pasture production lost per weed in each life stage (as weed density approaches zero), and τ is the maximum proportion of pasture-production loss as weed density approaches infinity (when the population reaches steady-state). Damage to pasture production can be reduced through control (u). The financial return (benefit) in any time period is:

$$B_t = \pi_{wf}(1 - D_t\{\mathrm{x}_t,\mathrm{u}_t\}) - C_{u,t} \qquad (3)$$

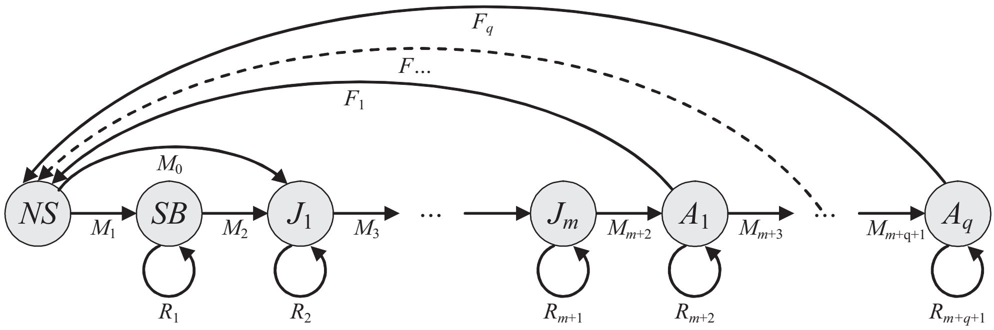

Figure 1. Life cycle diagram for chinee apple.

where π_{wf} is the weed-free grazing gross margin ha^{-1}, and C is the cost of control u in time t.

There are four different control methods considered in this study (Table 1). Note, ***no-control*** is for years where no action is taken as opposed to ***ignoring*** the infestation every year. More than one control is seldom used in the same year, but controls in consecutive years can be used as part of IWM. The variable costs for weed control are density-dependent, as more effort and materials are required for denser infestations. Fixed costs are unrelated to weed density, but do vary from treatment to treatment. These costs may include: transportation to site, setting up, etc. (Table 1). Control efficacies of the four control options are given as the proportion of individuals removed from the different life-cycle stages, after natural or climatic mortalities (Table 2) (Zull and Marshall unpublished data 2009).

Stochastic dynamic programming (SDP) is used to maximise the net benefit of weed control over time (t) by using various control methods (u), with a discount rate of 5%. The infestation is subject to the probable stochastic population growth based on the current state of the infestation (x_t) and the type of control used. The solution can be obtained by backwards induction, as the problem is autonomous, based on Markov chain processes where the future is given by the current state and is independent of the past (Bellman 1957). An optimal decision rule U*{X} is obtained based on the state of the infestation (x).

Table 1. Weed control options (u) and costs \$ ha^{-1} (C_u).

Control method (u)	Fixed costs (\$ ha^{-1})	Variable costs (\$ per 1% of weed density)
u_1 (No-control)	\$0	\$0
u_2 (Burn)	\$18	\$0
u_3 (Chemical)	\$15	\$9.85
u_4 (Mechanical)	\$200	\$2.00

Table 2. The efficacies of different chinee apple management options on each life stage in upland (non-riparian) zones.

Life stage	u_1	u_2	u_3	u_4
New seeds (*NS*)	0	0.70	0	0
Seedbank (*SB*)	0	0.70	0	0
Seedlings (J_1)	0	0.48	0.68	0.54
Small juveniles (J_2)	0	0.29	0.80	0.57
Medium juveniles (J_3)	0	0.11	0.90	0.70
Large juveniles (J_4)	0	0.05	0.92	0.75
Small adults (A_1)	0	0.01	0.89	0.83
Medium adults (A_2)	0	0.01	0.85	0.87
Large adults (A_3)	0	0.01	0.83	0.89
Largest adults (A_4)	0	0.01	0.82	0.90

RESULTS

The optimal decision rule U*{X} represents a 'package' of control options to be applied at any time to manage any infestation based on its current state (Odom *et al.* 2003). This package is the IWM discussed below.

Figure 2 shows the IWM (U*) of an upland chinee apple infestation over time, based on normal control costs and π_{wf} = \$80. The management decision rule (U*) was applied to a theoretical fully developed (steady-state) upland (non-riparian) chinee apple infestation using the full population model (Eq. 1). Note that all four control methods where used as part of IWM. However, these results are based on randomly chosen climatic events. Therefore, every simulation run will result in different control decision over time.

Using U* control decision will result in an optimal economic level of weed infestation (weed damage) with respect to the weed free grazing gross margins. To derive this optimal level of weed damage, the model was run for 400 iterations for each weed free grazing gross margin. There is a clear threshold where control is undertaken (Figure 3). After this point the optimal level of damage decreases as π_{wf} increases, but at a diminishing rate. Figure 3 shows that when π_{wf} = $80 weed damage to pasture production decreases from ~45% to an average of ~5% with U*.

The question remains as to how weed management decisions and the expected net present values (NPVs) change with respect to changes in π_{wf} and C_u. To answer this question, the SDP model was run for 400 iterations for each combination of π_{wf} and C_u to derive the expected NPVs. The results are used to determine the threshold frontier between controlling and ignoring an infestation (Figure 4). Reductions in weed control costs are presented as a percentage reduction in total weed control costs. All combinations of π_{wf} and C_u below and to the left of the threshold frontier should

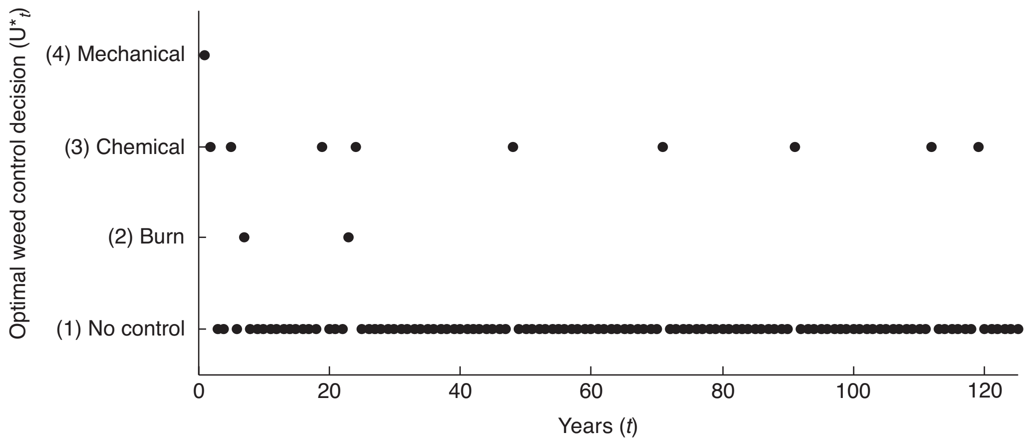

Figure 2. Optimal control decision U* for an upland chinee apple infestation. Population started from a steady state population, and climatic conditions were randomly selected. Simulation is based on normal control costs (C_u) and weed free grazing gross margins of π_{wf} = $80.

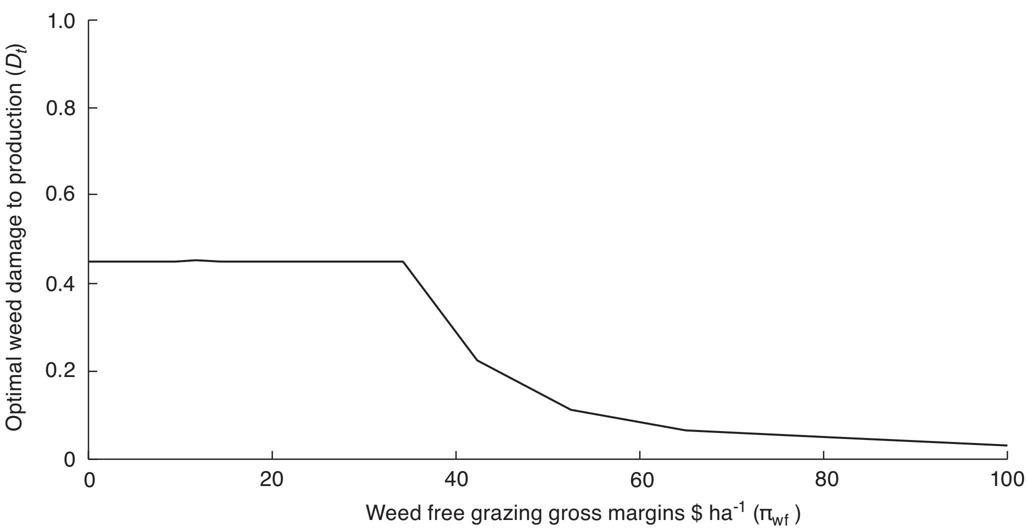

Figure 3. The optimal expected weed damage (proportion of lost pasture production) with U* control decisions with respect to changes in π_{wf} and using normal control costs.

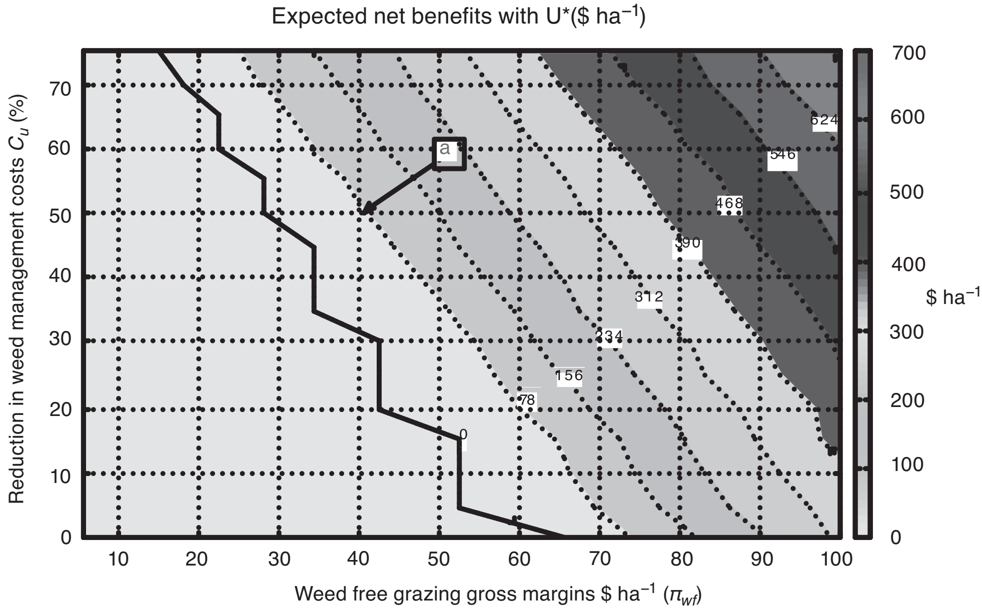

Figure 4. Management threshold based on net benefits of U* with respect to weed control costs (C_u) and weed free grazing gross margins (π_{wf}). The bold conditions dark line (zero value) represents the threshold frontier of weed management intervention. Below and to the left of this frontier it is optimal to ignore the infestation.

be ignored. Values given to the right represent the expected NPVs of using U* decision rules on a steady state (Figure 3 point 'a'), U* is expected to result in a net benefit of \$78 ha^{-1}.

DISCUSSION

This modelling framework has merged ecological and economic paradigms to derive an optimal set of weed control decisions (IWM) for chinee apple based on the cost and efficacy of weed control, the state of the infestation at any time, and the probability of rainfall events that result in episodic seedling recruitment.

In the northern Australian rangelands, weed-free grazing gross margins π_{wf} are under \$15 ha^{-1} for good-condition land. This analysis indicates that controlling upland chinee apple infestations will not return financial profits to graziers.

One of the market failures within rangeland grazing is that land prices are not affected by the presence of weed infestations, despite them offering lower productive output. If this was to change, it can easily be incorporated into the model, and the benefit of controlling weeds will increase.

This modelling framework can also be used to estimate the annual financial incentive (compensation) required by graziers from external stakeholders to control infestations. For example, with normal control costs the threshold frontier is at π_{wf} = \$65 ha^{-1} and if weed free grazing gross margins are only π_{wf} = \$15 ha^{-1}, the grazier would require an additional ~\$50 ha^{-1} p.a. to control an upland chinee apple infestation for environmental reasons that generate public (but not private) benefits.

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