Agricultural Systems 109 (2012) 1–8

Contents lists available at SciVerse ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Optimising control of an agricultural weed in sheep-production pastures

Morteza Chalak *, David J. Pannell

School of Agricultural and Resource Economics, Centre for Environmental Economics & Policy, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia

ARTICLE INFO

Article history:
Received 5 September 2011
Received in revised form 20 January 2012
Accepted 29 January 2012
Available online 2 March 2012

Keywords:
Weed
Blackberry
Optimisation
Stochastic
Agriculture

ABSTRACT

Optimal integrated control strategies for the weed blackberry (*Rubus anglocandicans*) infesting sheep pastures in Australia are analysed for a range of different circumstances. A wide range of control strategies with moderate to high costs and efficacies are analysed, including chemicals, mowing, grazing goats and biological control. The study employs a stochastic dynamic simulation model and a stochastic dynamic programming model to find the optimal control strategies under different levels of infestation. Results show that the application of a biological control agent (*Phragmidium violaceum*) increases expected net present value (ENPV) by so little that it is not worth introducing. Results indicate that for higher initial infestation areas, the optimal control strategies include fewer control options, resulting in lower cost but also less effective control. This is because the control costs are proportional to the infestation area, so applying expensive control strategies in high infestation area has lower net benefits. When the labour cost of spraying chemicals increases and infestation area is high, it is optimal to replace chemicals with mowing. If the efficacy of chemicals increases it is optimal to use less effective and cheaper chemicals.

1. Introduction

Invasive species are a significant threat to agriculture, as well as to natural ecosystems (Pannell, 1988; Pimentel, 2002; Sheppard et al., 2003). Invasive species are responsible for more than a third of the worldwide annual economic damage caused by invasive species, estimated at US$350 billion (Sheppard et al., 2003). Agricultural weeds in the USA reduce agricultural production by 12%, resulting in a loss of approximately $32 billion crop value annually, for a potential crop value of more than $267 billion per year (Pimentel et al., 2000).

Blackberry (*Rubus anglocandicans*) is a significant weed that causes damage to environment and agriculture in many countries including Australia (Reid, 2008), New Zealand (Quinn, 1997), Canada (Cogliastro et al., 2006), Latin America (Barreto, 2009), and United States (Yonce and Skroch, 1989; Glenn and Anderson, 1993; Pemberton, 2000). The cost of controlling blackberry plus the lost agricultural production in Australia was estimated at $41.5 million per year (James and Lockwood, 1998). In the central western area of the state of New South Wales alone, the value of the lost production plus the cost of controlling blackberry was estimated at $4.7 million per year (Vere and Dellow, 1984). There have been numerous studies on the ecological aspects and control of blackberry (e.g., Amor, 1972; Dellow et al., 1987; Nybom, 1988; Popay and Field, 1996; Evans et al., 2007; Gomez et al., 2008). However, there are few studies on the economics of blackberry control in agriculture. Vere and Dellow (1984), James and Lockwood (1998) and Ireson et al. (2007) present some economic impacts of blackberry in Australian agriculture. However, there has not previously been an economic study of the most cost-effective Integrated Weed Management (IWM) strategies for blackberry. To find the optimal management strategy, given the dynamic character of weed population, a dynamic analysis is required in which net present value (ENPV) of the agricultural activities over time is maximised.

Dynamic optimisation models have been used in a number of studies of weeds, including for the control of wild oats in the United States (Taylor and Burt, 1984), hardheads in Australia (Wu, 2001), foxtail and cocklebur in South Africa (McConnachie et al., 2003), Californian thistle in New Zealand (Chalak-Haghighi et al., 2008), soybean aphid in the north central region of the United States (Zhang et al., 2010) and annual ryegrass in Australia (Doole, 2008). In this paper we analyse the optimal IWM strategies for the control of blackberry in Australian sheep farms in a stochastic dynamic programming framework. Distinctive from most previous studies in weed control, we also take into account the portion of weed that can contribute to the diet of animal. A rare previous study to recognise positive as well as negative aspects of a weed was Abadi Ghadim and Pannell (1991).

Non-chemical options such as biological agents, mowing and grazing animals can be preferable to herbicides from an environmental perspective (Ehler, 1998; Thomas and Willis, 1998; Pemberton, 2000). However, their low and/or uncertain efficacy can be a concern to farm managers (Derera et al., 2000; Hart, 2001). In this paper we analyse whether these control options can be a

* Corresponding author. Tel.: +61 8 6488 5508; fax: +61 8 6488 1098.
E-mail address: morteza.chalak@uwa.edu.au (M. Chalak).

0308-521X/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.agsy.2012.01.010

part of optimal management strategies for the control of blackberry. Some chemicals are restricted to use in or near waterways. We analyse how exclusion of those chemicals affects the selection of optimal strategy.

Firstly we develop a stochastic dynamic simulation model that represents weed infestation. This model is spatially explicit and accounts for stochastic elements such as the introduction of new infestations and the probability of blackberry being removed by each control strategy. Secondly a stochastic dynamic optimisation model is developed that finds optimal integrated management strategies. Stochastic dynamic optimisation models have previously been used to identify optimal weed management strategies (e.g., Chalak et al., 2009, 2011; James et al., 2011). Stochastic simulation models have also been used by various authors to address weed management problems (e.g., Paice et al., 1998; Holst et al., 2007). In this study, we use a stochastic optimisation model that includes technical relationships estimated from a stochastic simulation model.

Our aim in this paper is firstly to identify the IWM strategies that are optimal in different circumstances. Secondly, we analyse whether non-chemical control options such as biological control, mowing and grazing goats are worthwhile economically. Thirdly, we test the sensitivity of optimal control strategies to changes in parameter values.

In the next section the methods are presented and the relationship between blackberry infestation area and benefit obtained from a sheep production pasture is explained. Then the stochastic dynamic simulation model and the stochastic dynamic optimisation model are presented. Next, we present results and a sensitivity analysis to show how changes in parameter values can affect optimal control options. Finally, the conclusions are presented.

2. Methods

2.1. Stochastic dynamics of blackberry

The model of blackberry spread represents an area of agricultural land (10 m × 100 m) adjacent to a waterway (which is the area most likely to become infested). This land has been divided to 1 m × 1 m square cells. The whole area consists of two zones. The first zone is the area within 5 m of the river. The second zone is the area that is 5–100 m from the river (Fig. 1). This distinction was made on the advice of a weed scientist that the land closest to a waterway is more likely to become infested by blackberry. New infestations are assumed to become established at random, potentially in any square metre of the land area, due to deposition of seeds in bird droppings or by flooding. Thus we assume that there are other infestations of blackberry in the district to serve as a source of seeds. The probability of a new infestation becoming established in any square metre of land is independently distributed from other land and is the same in every year. $\Pr_{n=1}$ and $\Pr_{n=2}$ are probabilities of a new infestations becoming established in any square metre of land in the first and second zones, respectively (Table 1).

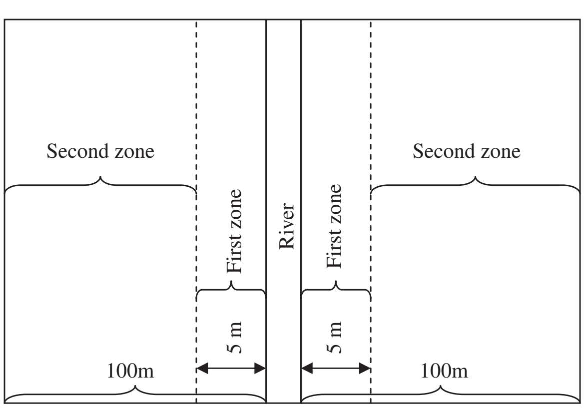

Fig. 1. Schematic representation of the riparian area. The first zone is land that is within the first 5 m from the river and the second zone is 5–100 m from the river.

L_{ijt} represents cells that are one square metre of land that is susceptible to blackberry invasion, indexed by coordinates i (along the river side) and j (distance from the river side) and time t. $L_{ijt} \in \{0, 1\}$ is the state of cell (i, j) at time t. $L_{ijt} = 1$ if the cell is infested and $L_{ijt} = 0$ if the cell is not infested by blackberry. When a cell is infested it cannot be utilised as forage for sheep.

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

$$\begin{cases} L_{ij0} = 1, & \text{if } (RAND) \leqslant \Pr_n \\ L_{ij0} = 0, & \text{otherwise} \end{cases} \tag{1}$$

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

$RAND$ is a randomly generated variable with uniform distribution.

$$0 \leqslant RAND \leqslant 1 \tag{2}$$

Cell L_{ijt} is infested if $RAND$ is less than 0.0016 for the first zone ($n = 1$) and is less than 0.000021 for the second zone ($n = 2$) (Table 1).

Once blackberry is established, the rate of spread (RS) is 2 m yr^{-1} in the first zone (RS_1) and 1 m yr^{-1} in the second zone (RS_2) due to decreased soil moisture (Table 1). Blackberry spreads sidewise to the neighbouring cells in four directions (north, east, west and south). $\Pr_s$ represents the annual probability of spread of blackberry from an infested cell to an uninfested neighbouring cell. This probability depends on the infestation area of blackberry. Based on the advice of weed scientists, we represent that the level of blackberry infestation asymptotically approaches a maximum percentage of the area, and that this maximum is less than 100%. As a consequence, as the infestation area of blackberry approaches the maximum level, the probability that new land will be invaded by its infested neighbour falls.

We assume that infestation area (w) is the proportion of the land that is infested by blackberry across the entire modelled area. Infestation area is defined as the ratio of infested cells to the total number of cells in the modelled landscape (L). Thus,

$$w = \frac{\sum_i^I \sum_j^J L_{ij}}{L} \tag{3}$$

where I and J represent the total number of rows and columns. The infestation area is the proportion of land that cannot be utilised for sheep grazing.

The relationship between $\Pr_s$ and the infestation area used in the model is based on the following four points, which were estimated by a collaborating weed scientist (see Table 1):

(1) $\Pr_s = 1$ when the infestation area across the entire modelled land is close to zero.
(2) $\Pr_s = 0$ when the infestation area reaches its carrying capacity (i.e. when blackberry infests 75% of the land).
(3) $\Pr_s = 0.9$ when blackberry infests 20% of the area.
(4) $\Pr_s = 0.3$ when blackberry infests 40% of the area.

These estimated values approximate the shape of a logit function. Thus the following logit function was used to represent $\Pr_s$.