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Optimal weed control under static and dynamic decision rules

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Abstract

Dynamic and static weed control decision rules are derived analytically and compared. The dynamic rule leads to increased farm profits and greater control of weeds and weed seeds than the static rule, while total herbicide use is unchanged. The magnitude of the differences is estimated for atrazine control of foxtail and cocklebur in corn production. Incorporating weed dynamics into weed control strategies increases farm profits between 1.0 and 1.4%. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Herbicide use; Weed control decision rules; Weed seed dynamics

1. Introduction

Herbicide use has enhanced agricultural productivity and benefited farmers and consumers. However, the intensive application of pesticides, particularly herbicides, has created concern about their environmental and health effects. One focus of public debates over pesticide policy has been the tradeoff between the productivity loss and the potential health and environmental benefits of reducing pesticide use. These cost and environmental concerns have provided farmers with a strong incentive to manage weed efficiently (Swinton and King, 1994b).

Integrated pest management (IPM) is an approach that generally includes pest monitoring and economic thresholds (Bauer and Mortensen, 1992; Coble and Mortensen, 1992; Osteen, 1993). The explicit connection between pesticide rates and pest numbers will generally reduce overall pesticide applications while maintaining production levels. IPM strategies have been developed for successful control of crop dis-

ease, insect damage, and weed damage (Gianessi and Greene, 1985; Ferguson, 1990). Most IPM strategies, especially for weed control, are static in that they do not consider future costs and benefits of actions taken today (e.g. Wiles et al., 1991; Wilkerson et al., 1991; Coble and Mortensen, 1992). Static decision models are appropriate if current actions do not affect future choices. For example, if future insect populations are independent of current insect numbers, then static insecticide strategies are optimal. But static strategies lead to suboptimal outcomes if future pest numbers depend on current pest numbers.

Population dynamics are particularly important for weeds because surviving weeds produce seeds that add to a soil's seed bank, thereby increasing future weed infestations (Fisher and Lee, 1981; Taylor and Burt, 1984; Pandey and Medd, 1991; Swinton and King, 1994a). Fisher and Lee (1981) examined weed and disease infestation in wheat by using a dynamic programming model. Taylor and Burt (1984) derived the near-optimal management strategies from a partially decomposed stochastic dynamic programming model for controlling wild oats in spring field. Their near-optimal decision rules depend on density of wild

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oats seed in the plow layer, soil moisture, and several other factors. Swinton and King (1994a) consider a 2-year period in their dynamic model and show that the optimal herbicide use in the first year not only depends on yield losses in the first year but also in the second year and, as a result, farmers considering weed seed dynamics may use more herbicide in the first year. Pandey and Medd (1991) conclude that it is necessary to consider multi-period effects to improve herbicide use decisions based on their simulation results. All previous analysis drew their conclusions from computer simulations. None examined the impacts of weed seed dynamics on total herbicide use and farm income analytically.

This paper generalizes available simulation-based results by deriving both static and dynamic optimal weed control decision rules. These decision rules are compared to demonstrate more generally how the incorporation of weed dynamics changes weed control strategies. We estimate the magnitude of likely changes by solving for optimal atrazine use to control foxtails and cocklebur infestations on corn. Our results show that dynamic weed control strategies will increase farm income without increasing total herbicide use.

There are large differences in weed management practices between developing and developed countries. In developed countries such as the US, farmers face more stringent environmental regulations on herbicide use (e.g. for atrazine, not more than 2.0 lb/acre per application, or 2.5 lb/acre per year), but they also have more herbicide choices and the option to switch to an alternative herbicide if one herbicide fails to achieve a desired control level. They rely heavily on herbicide rates specified on product labels in making herbicide decision. Nevertheless, there is still a large variation in herbicide application rates among farms as shown by the area data collected by the US Department of Agriculture. In developing countries, farmers typically face few herbicide use regulations, but they also have few herbicide choices. They often rely on changing application rates to achieve the desired levels of weed control. Since herbicide manufacturers rarely provide any legal guarantee on herbicide efficacy, farmers often choose their application rates based on their experiences, the herbicide costs, and their financial affordability. They also control weeds mechanically and manually.

The objective of this paper is not to derive guidelines for herbicide application rates, but instead to demonstrate the importance of considering weed seed dynamics in making herbicide use decisions. We compare the optimal levels of weed control under the static and dynamic decision rules and their resulting impacts on farm income. We show that farmers would control weeds to a lower level (either by increasing herbicide use or switching to an alternative pesticide) if weed seed dynamics are considered.

2. The model

Consider a typical grain farmer whose fields are infested with a weed. The farmer applies a herbicide to control the weed, with an objective of maximizing the present value of profits over a planning horizon of T years. The biological cycle of an annual weed consists of germination, growth, interference, and seed production (Bauer and Mortensen, 1992). A proportion of weed seeds in the soil seed bank germinates each spring. The seedlings are subject to several mortality factors including frost, drought, and fungal infection. The surviving seedlings compete with the crop if not controlled. Let S_t denote the number of seeds (the 'seed bank') at the beginning of the planting season in year t , and let m be the proportion of weed seeds that germinate and survive in the absence of herbicide treatments. The factors that affect m include weather, the age distribution of the weed seed population, and the depth at which the seeds are buried in soil.

Weed seedlings can be controlled by herbicide treatments. The most commonly used functional form for the herbicide rate response function is the exponential (Moffitt et al., 1984; Moffitt, 1986, 1988; Osteen et al., 1988; Gillmeister et al., 1990; Deen et al., 1993). Let H_t be herbicide usage, the number of weeds that survive to compete with the crop under this functional form assumption can be written as $W_t = mS_t e^{-cH_t}$, where c is a positive constant that depends on the herbicide used and the weed species. In this analysis, we assume that the optimal weed densities are achieved by changing herbicide application rates. If farmers also change herbicides to achieve the desired level of weed control, variable H_t can be interpreted as the 'toxicity' of the herbicide used. In this case, the

optimal weed density can be achieved by changing either the application rate or the herbicide used.

Surviving mature weeds produce fresh seeds for the soil seed bank, which starts the cycle again in the following spring. The seed bank density at the beginning of next planting season (S_{t+1}) is equal to the seed bank density in year t (S_t), minus the number of seeds lost from weed seedling germination and mortality factors (mS_t), plus the seed reproduction (kW_t), where k is the number of seeds each weed produces. For simplicity, we assume that all seeds either germinate or are dead forever.¹ Under this assumption, the seed bank density at the beginning of next planting season can simply be written as $S_{t+1} = kW_t = kmS_t e^{-cH_t}$.

Competing biological theories support hyperbolic yield loss functions (Cousens, 1985; Wilkerson et al., 1991; Coble and Mortensen, 1992; Swinton and King, 1994b). So in this study the yield loss function is assumed to take the hyperbolic form

$$D(W) = \frac{W}{100(a + bW)}, \quad (1)$$

where $D(W)$ is the percentage yield loss for a given value of W , $(1/a)$ the marginal percentage yield loss as weed density approaches zero, and $(1/b)$ is the maximum percentage yield loss from weeds (Swinton and King, 1994a). By using the damage and weed control functions, the yield response function can be written as $Y_t = Y_{0t}[1 - D(mS_t e^{-cH_t})]$, where Y_{0t} is the weed-free crop yield.

In general, germination rate m , herbicide efficacy c , and weed-free yield Y_{0t} are random parameters because they are affected by rainfall, temperature, and other factors that are not known with certainty. The impacts of uncertainty about these parameters on herbicide use have been examined by Feder (1979), Deen et al. (1993), Swinton and King (1994b), and several other studies. In this paper we focus on the importance of considering weed seed dynamics in herbicide use decisions. We ignore the uncertainty in order to derive the dynamic and static herbicide decision rules. By comparing these decision rules, we are able to demonstrate the importance of considering

weed seed dynamics in herbicide use decisions. Sensitivity analysis is conducted with these parameters in order to examine the robustness of our results.

Assume that the farmer's objective is to maximize the present value of profits, then his or her herbicide use decision can be represented by

$$\begin{aligned} \text{Max}_{H_t} \sum_{t=1}^T \rho^t \{ & P_t Y_{0t} [1 - D(mS_t e^{-cH_t})] \\ & - V_t H_t - C_{0t} \}, \end{aligned} \quad (2)$$

$$\text{s.t. } S_{t+1} - S_t = (mk e^{-cH_t} - 1)S_t, \quad (3)$$

$$S_1 = S_1^0, \quad (4)$$

where ρ is the discount factor, V_t the herbicide price in year t , C_0 the production cost excluding herbicides, and S_1^0 is the initial seed bank density. This maximization problem is an optimal control problem, in which S is the state variable, H the decision variable, Eq. (3) the equation of motion, and Eq. (4) is the initial condition.

The problem can be solved using optimal control techniques. The Hamiltonian function for the maximization problem is

$$\begin{aligned} L_t = \rho^t \{ & P_t Y_{0t} [1 - D(mS_t e^{-cH_t})] - V_t H_t - C_{0t} \} \\ & + \lambda_t (mk e^{-cH_t} - 1)S_t, \end{aligned} \quad (5)$$

where $\lambda_t \leq 0$ is the Lagrangian multiplier and can be interpreted as the marginal cost of seed bank density. The first-order necessary conditions for the maximization problem are

$$\begin{aligned} \frac{\partial L_t}{\partial H_t} = \rho^t \{ & P_t Y_{0t} D'(mS_t e^{-cH_t}) cmS_t e^{-cH_t} - V_t \} \\ & - \lambda_t cmkS_t e^{-cH_t} = 0, \end{aligned} \quad (6)$$

$$\begin{aligned} \frac{\partial L_t}{\partial S_t} = -\rho^t P_t Y_{0t} D'(mS_t e^{-cH_t}) m e^{-cH_t} \\ & + \lambda_t (mk e^{-cH_t} - 1) = -(\lambda_t - \lambda_{t-1}), \end{aligned} \quad (7)$$

$$\frac{\partial L_t}{\partial \lambda_t} = (mk e^{-cH_t} - 1)S_t = S_{t+1} - S_t. \quad (8)$$

Eq. (6) can be rewritten as

$$\rho^t P_t \frac{\partial Y_t}{\partial H_t} + \lambda_t \frac{\partial S_{t+1}}{\partial H_t} = \rho^t V_t. \quad (9)$$

¹ This assumption may be more valid for some weed species than for others. For green and yellow foxtails, one of the weeds we will examine in our numerical example, 53.8% of seeds will emerge. For those unemerged seeds, 71.4% die (Swinton and King, 1994a).

The first term on the left-hand side of Eq. (9) is the marginal value product of herbicide use, and the second term is the marginal value of seed bank density reduction in year $t+1$ from increased herbicide use in year t . Thus, Eq. (9) indicates that the optimal herbicide use decision must account for the benefits of reducing crop losses in both current and following seasons. Given the seed bank density at the beginning of a year, a dynamic weed control strategy leads to at least as much herbicide use in year t than a static strategy. However, this does not necessarily imply that a dynamic weed control strategy will result in more total herbicide use in the planning horizon because dynamic and static weed control strategies may lead to different time paths of the weed seed bank density.

Eq. (7) can be rewritten as

$$\rho^t P_t \frac{\partial Y_t}{\partial S_t} + \lambda_t \frac{\partial S_{t+1}}{\partial S_t} = \lambda_{t-1} \quad (10)$$

The first term on the left-hand side of Eq. (10) is the marginal revenue reduction due to an increase in seed bank density in year t , and the second term is the increase in the marginal cost of seed bank density in year $t+1$ due to an increase in seed bank density in year t . Thus, Eq. (10) indicates that seed bank density should be controlled at the level at which the sum of marginal revenue reduction in year t and the increase in the marginal cost of weed seed bank density in year $t+1$ equals the marginal cost of weed seed bank density in year $t-1$.

Multiplying both sides of Eq. (7) by cS_t and adding it to Eq. (6) gives $0 = \rho^t V_t + cS_t \lambda_{t-1}$ or $\lambda_{t-1} = -\rho^t V_t / cS_t$. By substituting this result, the damage function, and $S_{t+1} = kW_t = kmS_t e^{-cH_t}$ into Eq. (6) and rearranging terms, we get

$$b^2 W_t^2 + (2ab - d_t) W_t + a^2 = 0, \quad (11)$$

where

$$d_t = \frac{acP_t Y_{0t}}{100(V_t - \rho V_{t+1})}. \quad (12)$$

Eq. (11) has a positive solution if and only if $d_t \geq 0$ and $(2ab - d_t)^2 - 4a^2 b^2 \geq 0$, which together implies that $d_t \geq 4ab$. Under this condition, Eq. (11) has two solutions, but only the following one satisfies the

second-order necessary condition:²

$$W_t^* = \frac{(d_t - 2ab) - \sqrt{(d_t - 2ab)^2 - 4a^2 b^2}}{2b^2}. \quad (13)$$

As the farmer does not benefit from a lower seed bank density at the end of the planning horizon, the farmer will keep the weed density at the level that maximizes the current year's profit. So, for year T , W_T^* is given by Eq. (13) with $d_T = acP_T Y_{0T} / 100V_T$. This result will be proved in the next section.

By substituting the optimal weed density into $S_t = kW_{t-1}$ and $W_t = mS_t e^{-cH_t}$, we obtain the optimal time paths of seed bank density and herbicide use

$$S_t^* = kW_{t-1}^*, \quad t = 2, \dots, T, \quad (14)$$

$$H_1^* = -\frac{1}{c} \ln \left(\frac{W_1^*}{mS_1^0} \right), \quad (15)$$

$$H_t^* = -\frac{1}{c} \ln \left(\frac{W_t^*}{mS_t^*} \right) = -\frac{1}{c} \ln \left(\frac{W_t^*}{mkW_{t-1}^*} \right), \quad t = 2, \dots, T \quad (16)$$

The total amount of herbicide used in the planning horizon is

$$\begin{aligned} TH_T^* &= \sum_{t=1}^T H_t^* \\ &= -\frac{1}{c} \ln \left(\frac{W_T^*}{mkW_{T-1}^*} \frac{W_{T-1}^*}{mkW_{T-2}^*} \dots \frac{W_2^*}{mkW_1^*} \frac{W_1^*}{mS_1^0} \right) \\ &= -\frac{1}{c} \ln \left(\frac{W_T^*}{m^T k^{T-1} S_1^0} \right). \end{aligned} \quad (17)$$

Eqs. (12) and (14) indicate if the input and output prices are constant in the planning horizon, then optimal weed and seed bank densities are constant from Years 2 to $T-1$ because d_t is a constant. The farmer adjusts weed and seed bank densities to their optimal levels in the first year by applying whatever amount of herbicide needed. The farmer will then use $(1/c) \ln(mk)$ units of herbicide every year until year $T-1$. This quick adjustment to the optimal levels may not be

² The other solution to Eq. (11) is $W_t = [(d_t - 2ab) + \sqrt{d_t(d_t - 4ab)}] / 2b^2$, at which the Hamiltonian function (5) is convex (i.e. $\partial^2 L_t / \partial H_t^2 > 0$).

achieved in reality because of herbicide use regulations. In this situation, the adjustment to the optimal level should be made as quickly as possible.

3. The consequence of ignoring the multi-season effects of herbicide use

Suppose the farmer ignores the multi-season effects of herbicide use in weed control decisions. The decision problem for year t becomes

$$\begin{aligned} \max_{H_t} \pi_t = & P_t Y_{0t} [1 - D(mS_t e^{-cH_t})] \\ & - V_t H_t - C_{0t}. \end{aligned} \quad (18)$$

The first-order condition for this maximization problem is

$$P_t Y_{0t} D'(mS_t e^{-cH_t}) c - V_t = 0 \quad (19)$$

By substituting Eq. (1) into Eq. (19) and noting that $W_t = mS_t e^{-cH_t}$, we get

$$b^2 W_t^2 + (2ab - d_t^0) W_t + a^2 = 0, \quad (20)$$

where

$$d_t^0 = \frac{acP_t Y_{0t}}{100V_t}. \quad (21)$$

Eq. (20) has a positive solution if and only if $d_t^0 \geq 0$ and $(2ab - d_t^0)^2 - 4a^2b^2 \geq 0$, or $d_t^0 \geq 4ab$. Under this condition, the optimal weed density under the static rule is³

$$W_t^0 = \frac{(d_t^0 - 2ab) - \sqrt{(d_t^0 - 2ab)^2 - 4a^2b^2}}{2b^2} \quad (22)$$

The seed bank density and herbicide use under the static rule are

$$S_t^0 = kW_{t-1}^0, \quad (23)$$

$$H_1^0 = -\frac{1}{c} \ln \left(\frac{W_1^0}{mS_1^0} \right), \quad (24)$$

$$\begin{aligned} H_t^0 = & -\frac{1}{c} \ln \left(\frac{W_t^0}{mS_t^0} \right) = -\frac{1}{c} \ln \left(\frac{W_t^0}{mkW_{t-1}^0} \right), \\ & t = 2, 3, \dots, T \end{aligned} \quad (25)$$

The total amount of herbicide used in T years is

$$TH_T^0 = \sum_{t=1}^T H_t^0 = -\frac{1}{c} \ln \left(\frac{W_T^0}{m^T k^{T-1} S_1^0} \right). \quad (26)$$

Now, we compare this set of results with those derived in the last section under the dynamic decision rule. To compare the weed density, we define

$$W(d) = \frac{(d - 2ab) - \sqrt{d^2 - 4abd}}{2b^2}. \quad (27)$$

Note that $W(d_t) = W_{1t} = W_t^*$ is the optimal weed density under the dynamic decision rule, and $W(d_t^0) = W_t^1 = W_t^0$ is the optimal weed density under the static decision rule. Since $W(d)$ is a decreasing function of d (i.e. $W'(d) < 0$), we have

$$W_t^* = W(d_t) < W(d_t^0) = W_t^0, \quad 1 < t < T. \quad (28)$$

Also, because $S_t = kW_t$,

$$S_t^* < S_t^0, \quad 1 < t < T. \quad (29)$$

Thus, the dynamic decision rule results in greater control of both weed and seed bank densities than the static decision rule.

To compare total herbicide use under the two decision rules, assume that input and output prices are constant in the planning horizon. As in the dynamic case, the farmer using the static rule would maintain weed and seed bank densities, W_t^0 and S_t^0 , at constant (but higher) levels. And in the first year, the farmer would adjust weed and seed bank densities to the optimal levels by applying the required amount of herbicide. Since $W_1^0 < W_1^*$, $H_1^0 = -(1/c) \ln(W_1^0/S_1^0) < H_1^* = -(1/c) \ln(W_1^*/S_1^0)$. That is, farmers using the static decision rule would use less herbicide in the first year than under the dynamic decision rule. For Years 2 to $T-1$, the two decision rules result in identical herbicide rates:

$$H_t^0 = -\frac{1}{c} \ln \left(\frac{1}{mk} \right) = H_t^*, \quad t = 2, \dots, T-1.$$

In the last year of the planning horizon, the optimal weed density converges to the optimal static level. However, because the seed bank density is lower at the beginning of year T under the dynamic rule, the farmer will use less herbicide in year T . The difference between herbicide use in these two cases is

³ Again, the other solution does not satisfy the second-order necessary condition for the maximization problem in Eq. (18).

$$\begin{aligned} \text{TH}_T^* - \text{TH}_T^0 &= -\frac{1}{c} \ln \left(\frac{W_T^*}{k^{T-1} S_1} \right) - \frac{1}{c} \ln \left(\frac{W_T^0}{k^{T-1} S_1} \right) \\ &= \frac{1}{c} \ln \left(\frac{W_T^0}{W_T^*} \right) = 0. \end{aligned} \quad (30)$$

This implies that the additional amount of herbicide used in year 1 under the dynamic weed control strategy equals the additional amount of herbicide used in year T under the static weed control strategy.

Profit for each year can be estimated for the two decision rules from the optimal weed densities and herbicide rates. As the present value of profits in the planning horizon is maximized under the dynamic decision rule, producers will make more profit by using this decision rule. The difference between the net present values of profits under these two decision rules is

$$\text{NPV}_D - \text{NPV}_S = \sum \rho^t \{ P_t Y_{0t} [D(W_t^0) - D(W_t^*)] + V_t (H_t^0 - H_t^*) \}, \quad (31)$$

where NPV_D and NPV_S are the net present values of profits under the dynamic and static decision rules.

4. Weed control in Iowa corn production

In this section we present a numerical example to illustrate the difference between the static and dynamic weed control decision rules and their impacts on weed control and farm income. The numerical example is based on control of two weeds, foxtail and cocklebur, for corn production in Iowa, USA, where the data are available. Foxtail represents grass weeds, and cocklebur represents broadleaf weeds. The herbicide used to control these weeds is assumed to be atrazine,

which has been widely used in the US and most frequently detected in groundwater (Kolpin et al., 1994). Atrazine application rates, weed and seed bank densities, and per-acre net returns under the static and dynamic decision rules are predicted for the period of 1998–2002 by using price and cost projections of the Food and Agricultural Policy Research Institute (FAPRI). A planning horizon of 5 years is assumed.

Data needed for this application include biological and biochemical parameters a , b , c , k , and m , weed-free yield Y_{0t} , corn and atrazine prices (P_t and V_t), and discount rate (ρ_t) from 1998 to 2002. Biological and biochemical parameters used in the simulations are shown in Table 1. These parameters are obtained from several sources. Atrazine efficacy parameter c for foxtail and cocklebur was estimated based on application rates and efficacy percentages reported in the 1997 Guide for Herbicide Use in Nebraska (Nebraska Cooperative Extension 1998). The maximum yield loss is assumed to be 70% for both foxtail and cocklebur infestation, which implies that parameter b in the yield loss functions equals $1/70$. The marginal yield loss as weed density approaches zero (i.e. $1/a$) and the number of seeds each weed produces (k) for foxtail were taken from Swinton and King (1994a).

The projection of corn price for 1998–2002 was taken from the Food and Agricultural Policy Research Institute (FAPRI, 1996). FAPRI projections are based on a number of assumptions about the general economy, domestic and foreign agricultural policies, and weather and technologic changes. It is assumed that current agricultural policies will continue in the US and other trading nations. Average weather conditions and historical rates of technological changes will prevail during the projection period. Weed-free yields from 1998 to 2002 were estimated by adjusting the

Table 1
Biological and biochemical parameters of foxtail and cocklebur

Parameter	Foxtail	Cocklebur
$1/a$ (marginal yield loss (%) as weed density approaches zero)	0.20 ^a	0.75
$1/b$ (yield loss (%) as weed density approaches infinite)	70	70
c (herbicide efficacy)	0.78	0.93
k (the number of seeds each weed produces)	99 ^a	50
m (% of seeds that germinate and survive)	6	8

^a Swinton and King (1994a).

FAPRI yield projections by the percentage yield loss due to weeds in Iowa (Bridges and Anderson, 1992). Bridges and Anderson (1992) estimate that corn loss due to weeds in Iowa is 7% under current practices. The costs for all other inputs except atrazine in 1993, C_{0t} , were estimated by using data collected in the Iowa MAX program (US Department of Agriculture, 1993). The values of C_{0t} from 1998 to 2002 were estimated by assuming that it will follow the same trend as the variable costs of corn production as projected by FAPRI. The 1997 price of atrazine was taken from Nebraska Cooperative Extension. The atrazine prices from 1998 to 2002 were estimated by assuming that it will follow the same trend as the pesticide costs as projected by FAPRI. The discount rate ρ_t is set to $1/(1+r_t)$, where the interest rate r_t is assumed to be 8%.

5. Results and discussion

Table 2 presents the time paths of atrazine application rate, weed and seed bank densities, and per-acre net return under the static and dynamic decision

rules for controlling foxtails and cocklebur in Iowa corn production. The dynamic decision rule results in lower weed and seed bank densities and a higher net present value of profits than the static decision rule. Considering weed seed dynamics in foxtail control would increase the net present value of profits by US\$ 1.12/acre in the 5-year period, which represents a 1.42% increase over the net present value of profits under the static decision rule. The income effect is smaller in cocklebur control, where the net present value of profits increases by US\$ 0.93/acre in the 5-year period, a 1.02% increase. The small increase in profit is consistent with previous findings. For example, Cousens et al. (1986) found that compared with spraying indiscriminately at the label dose every year, the dynamic threshold decision rule lead to only a small saving in the control of *Avena fatua* in Winter Wheat; whether this saving is sufficient to cover the cost of assessment of weed density is unknown.

As pointed out by Pandey and Medd (1991), variability in herbicide efficacy is one of the dominant sources of risk in weed control. To examine how variability in herbicide efficacy affects the relative advantage of the dynamic decision rule, sensitivity

Table 2
Weed control and per-acre net returns under the static and dynamic decision rules

Year	Static model				Dynamic model			
	Seeds (number/m ²)	Weeds (plants/m ²)	Atrazine (lb/acre)	Net return (US\$/acre)	Seeds (number/m ²)	Weeds (plants/m ²)	Atrazine (lb/acre)	Net return (US\$/acre)
<i>Foxtail</i>								
1998	600 ^a	6.53	2.19	15.13	600 ^a	5.99	2.30	15.12
1999	647	6.75	2.24	4.26	593	6.19	2.24	4.59 ^b
2000	669	6.53	2.33	15.60	613	5.98	2.33	15.94
2001	646	6.42	2.31	23.48	592	5.88	2.31	23.82
2002	635	6.16	2.34	37.84	582	6.16	2.22	38.20
Total	3197	32.39	11.40	96.31	2980	30.20	11.40	97.67
Present value				78.90				80.02
<i>Cocklebur</i>								
1998	100 ^a	1.45	1.83	16.88	100 ^a	1.33	1.93	16.87
1999	73	1.50	1.46	7.37	67	1.38	1.46	7.65 ^b
2000	75	1.45	1.53	18.78	69	1.33	1.53	19.06
2001	73	1.43	1.51	26.68	67	1.31	1.51	26.97
2002	71	1.37	1.53	41.11	65	1.37	1.44	41.41
Total	392	7	7.86	110.83	367	6.72	7.86	111.96
Present value				91.21				92.14

^a These values denote S_1^0 .

^b The net return for 1999 is lower because of lower projected corn price for the year by FAPRI.

Table 3
The sensitivity analysis with the atrazine efficacy parameter

Year	Difference in weed density under static and dynamic rules			Difference in atrazine use under static and dynamic rules			Difference in per-acre net return under dynamic and static rules		
	$c=0.50$	$c=0.78$	$c=1$	$c=0.50$	$c=0.78$	$c=1$	$c=0.50$	$c=0.78$	$c=1$
<i>Foxtail</i>									
1998	0.89	0.55	0.42	−0.18	−0.11	−0.09	−0.02	−0.01	−0.01
1999	0.92	0.56	0.43	0.00	0.00	0.00	0.53	0.33	0.26
2000	0.89	0.55	0.42	0.00	0.00	0.00	0.54	0.34	0.26
2001	0.88	0.54	0.41	0.00	0.00	0.00	0.54	0.34	0.26
2002	0.00	0.00	0.00	0.18	0.11	0.09	0.57	0.36	0.28
Present value							1.78	1.12	0.87
	$c=0.75$	$c=0.93$	$c=1.25$	$c=0.75$	$c=0.93$	$c=1.25$	$c=0.75$	$c=0.93$	$c=1.25$
<i>Cocklebur</i>									
1998	0.15	0.12	0.09	−0.12	−0.09	−0.07	−0.01	−0.01	−0.01
1999	0.16	0.12	0.09	0.00	0.00	0.00	0.35	0.28	0.21
2000	0.15	0.12	0.09	0.00	0.00	0.00	0.35	0.28	0.21
2001	0.15	0.12	0.09	0.00	0.00	0.00	0.35	0.28	0.21
2002	0.00	0.00	0.00	0.12	0.09	0.07	0.38	0.30	0.22
Present value							1.17	0.93	0.69

analysis was conducted with the atrazine efficacy parameter. The results are shown in Table 3 and Figs. 1 and 2. Three values of parameter c are simulated for controlling each weed. In the baseline simulations parameter c is assumed to take the medium value (0.78 for foxtail and 0.93 for cocklebur), which correspond to 82 and 87% of efficacy with a 2.2 lb of application rate. The results clearly show that the lower the herbicide efficacy, the larger the difference in weed and seed bank densities and per-acre net return under the static and dynamic decision rules. For example, when the atrazine efficacy is reduced from 89% ($1 - e^{-1 \times 2.2} = 0.89$) to 67%, the difference in net present value under the dynamic and static decision rules increases from US\$ 0.87 to 1.78 in the control of foxtails. Thus, it is more advantageous to use the dynamic decision rule when the herbicide use efficacy is low.

The intuition behind this result is that the static decision rule always results in insufficient control of weeds because it does not take into account the benefit of lower seed densities in subsequent years. When the herbicide efficacy is lower, the degree of the insufficient control increases, which results in a larger difference in weed and seed bank densities and per-acre net return under the dynamic and static decision rules.

The initial seed bank density (S_1^0) is a crucial variable in weed management models and varies dramatically across fields (Swinton and King, 1994a). In the baseline simulations, the initial seed bank density is assumed to be 600 seeds/m² for foxtails and 100 for cocklebur. Sensitivity analysis was conducted with the initial seed bank densities. As shown by Eqs. (13) and (22), changes in the initial seed bank densities do not change the optimal weed density under both the dynamic and static decision rules. However, a higher initial seed bank density increases herbicide use in the first year under both the dynamic and static decision rules (see Eqs. (15) and (24)). As a result, it reduces the per-acre net return under both rules. Without herbicide use restrictions, the farmer would control weeds to the optimal levels in the first year and use same amount of herbicide in the subsequent years. This result depends on the assumption that seeds live for only 1 year. Without this assumption, herbicide uses in subsequent years may also be affected. Although the herbicide use and per-acre net return in the first year are sensitive to the initial weed density under both static and dynamic decision rules, the difference in herbicide use and net return (both total and first year) under the dynamic and static decision rules are not affected by the initial seed bank density at all (see Eqs. (15),

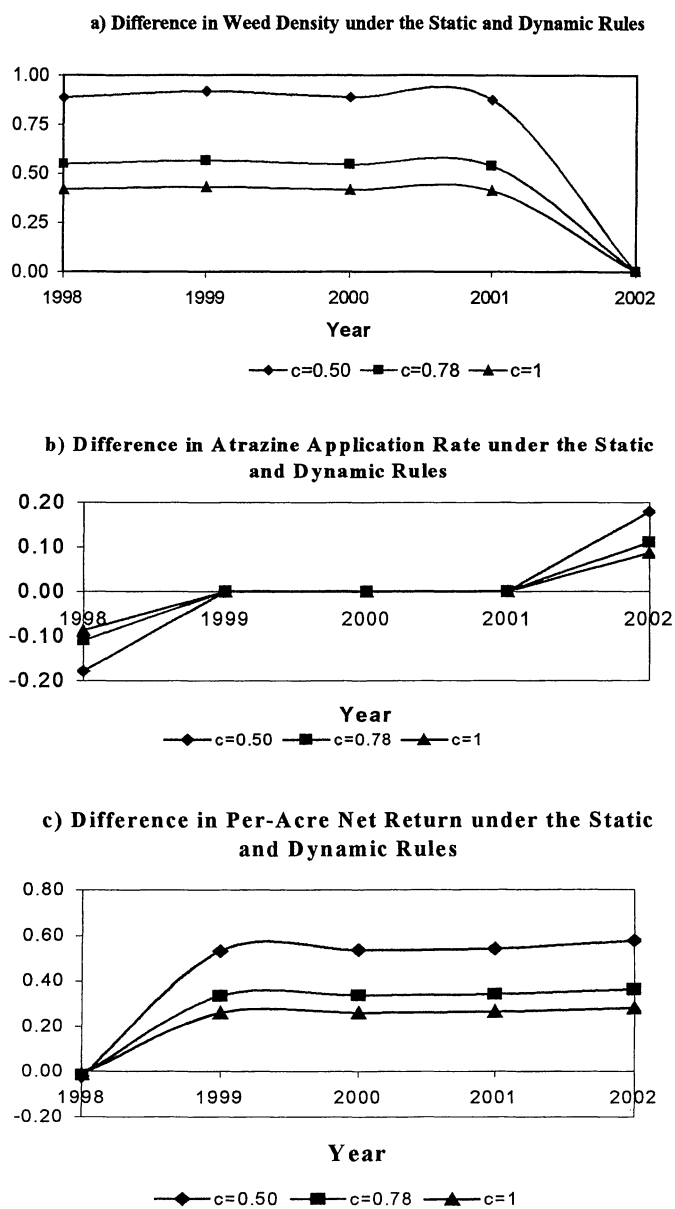


Fig. 1. Sensitivity analysis with atrazine efficacy in controlling foxtails.

(24), (30) and (31)). Thus, changes in the initial seed bank density do not change the relative advantage of the dynamic and static decision rules.

Sensitivity analysis was also conducted with respect to changes in the seed germination rate (m) and the number of seeds each weed produces (k). As shown by Eqs. (13) and (22), changes in m or k do not change

the optimal weed density under both dynamic and static decision rules, but these changes will affect herbicide use and farm income (see Eqs. (14)–(17) and (23)–(26)). As the initial seed bank density, these parameters do not affect the relative advantage of the dynamic and static decision rules because they do not change the difference in herbicide use and net present

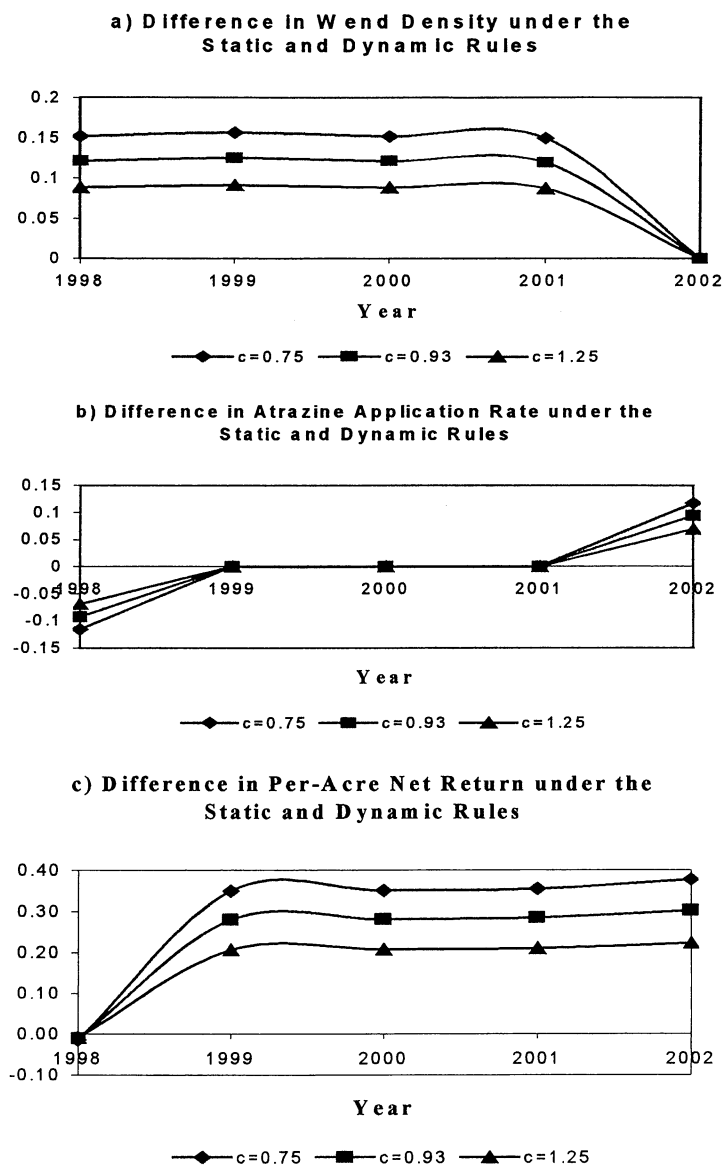


Fig. 2. Sensitivity analysis with atrazine efficacy in controlling cocklebur.

value of profits under the dynamic and static decision rules.

6. Concluding remarks

This paper develops and solves a dynamic optimization model to compare outcomes under the static and

dynamic weed control decision rules. The dynamic rule leads to increased farm profits and greater control of weeds than the static rule without increasing total herbicide use. The model was applied to control of foxtails and cocklebur with atrazine in Iowa corn production. The dynamic decision rule increases the net present value of profit by 1.02% in the control of cocklebur and 1.44% in the control of foxtails.

Potential benefits of adopting the dynamic weed control decision rule will depend on the cropping systems to which it is applied. The benefits are likely to be large when it is applied to a high-value crop that is more likely to be infested with weeds and is treated with large amount of herbicides (i.e. some vegetables or nursery crops). However, for those cropping systems that are less likely to be infested with weeds or whose weeds can be successfully controlled with non-chemical methods such as crop rotations, potential benefits of adopting the dynamic decision rule would be smaller.

Sensitivity analysis was conducted with respect to herbicide efficacy, the initial seed bank density, the germination rate, and the number of seeds each weed produces. The results show that the lower the herbicide efficacy, the higher the degree of insufficient control of weeds under the static decision rule, suggesting that it is more advantageous to use the dynamic decision rule when the herbicide efficacy is low. Although the initial seed bank density, the germination rate, and the number of seeds each weed produces all affect the rate of herbicide use and farm net return, these parameters do not change the differences in herbicide use and farm net return under the static and dynamic decision rule. Thus, they do not change the comparative advantage of a dynamic weed control decision rule.

Much information on weed control strategies has been provided to farmers by cooperative extension agencies in the US. The suggested treatment strategies often take the form of a threshold decision rule: if weed density exceeds a threshold, then apply the recommended pesticide dosage, otherwise, do not treat (Moffitt, 1988). Despite promise of economic and environmental benefits associated with the use of the threshold decision rule and other integrated pest management (IPM), producer adoption remains low for some crops (McNamara et al., 1991; Szmedra et al., 1991). Several explanations have been suggested, including (a) lack of access to accurate information required to integrate IPM into current management practices, and (b) perception of increased risk associated with IPM adoption (Greene et al., 1985; Musser et al., 1986; McNamara et al., 1991). Our results suggest that failure to develop successful IPM strategies may be another possible reason. We have shown that the recommended weed control threshold would be too low if weed seed dynamics is ignored. Some suggested strategies may have this

problem because thresholds are often determined without considering weed seed dynamics and multiple-year profit effects (Cousens et al., 1986; Moffitt, 1988).

The dynamic model presented in this paper abstracts from several important facets of weed control decisions. Intraseason decisions about herbicide application modes such as pre- or post-emergence are not represented in this analysis. Uncertainties about weather and input and output prices and farmers' risk preferences are ignored. Extensions of this model that incorporate these factors would be useful to determine the robustness of our results.

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