Proactive or Reactive? Optimal Management of an Invasive Forest Pest in a Spatial Framework

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Abstract: This paper offers a preliminary investigation into the conditions under which it might be optimal to engage in proactive management of a non-timber forest resource in the presence of an invasive species whose spread is unaffected by management action. Proactive management is defined as treating an uninfected area in order to encourage healthy ecosystem function, given that the arrival of the invasive is inevitable. Inspired by the problem of white pine blister rust in the Rocky Mountain west, the model was solved under varying assumptions concerning the scale of management action, benefit and costs, the discount rate, and uncertainty of spread. Results showed that proactive strategies tended to be optimal when, ceteris paribus, a) more resources are available for treatment; b) the costs of treatment are rapidly increasing in forest health, or conversely, the benefits of healthy and unhealthy stands are relatively similar; and c) the discount rate is low. The introduction of uncertainty did not significantly affect the likelihood of a proactive management strategy being optimal, but did show that the conditional probabilities of infection play important role in the decision of which uninfected stand should be treated if a choice is available to the manager.

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1. Introduction

The emergence of the "global economy", highly identified with increased movement of goods and services, has also increased the probability of non-marketable organisms establishing themselves in areas outside of their native habitat (Mack et al. 2000, Mack and Lonsdale 2001). In some cases, economic damages associated with such movement and establishment will be minimal.[1] In others, however, conditions such as a lack of natural enemies for the non-native species and/or a lack of resistance in native organisms to the new species may be sufficient to render significant damages, and earn the label of invasive pest (Schoettle and Sniezko, 2007).

Forests are among the ecosystems being impacted by non-native pests and pathogens. Numerous non-native arthropod pests and non-native plant species have already disrupted many forest ecosystems throughout North America. Examples include *Cryphonectria parasitica* (Murrill) Barr, the fungal pathogen responsible for chestnut blight of American chestnut trees; *Ophiostoma novo-ulmi* Brasier, the fungal pathogen responsible for the Dutch elm disease of American elm and other native elm species; and *Cronartium ribicola* J.C. Fisch., the fungal pathogen that causes white pine blister rust (WPBR) and cycles between native 5-needle white pines, currants, and gooseberries. The non-native pathogens have severely reduced some forest species populations, altered forest composition, and threatened the habitats of endangered animals (Liebold et al. 1995).

Most invasive species management strategies focus on (1) prevention, (2) early detection and eradication, (3) containment and control, and when those efforts are unsuccessful, (4) mitigation of impacts and (5) restoration of the degraded forest (Schoettle and Sniezko, 2007). However, in some cases (such as with WPBR), (1)-(3) have proven challenging, with no

[1] Of course, such damages can be to marketable and/or non-marketable ecosystem services.

effective strategies identified. As such, there is a growing interest in preemptively managing ecosystems to mitigate the potential negative impacts of invasives before significant damage occurs. However, only recently have the physical outcomes of these forest management techniques been explored, and the economic conditions under which such "proactive management" is optimal have not been analyzed (Schoettle and Sniezko, 2007).

This paper provides a preliminary model that can be used to analyze the conditions under which it might be optimal to pursue a proactive, as opposed to reactive, management strategy in the case of an invasive forest pathogen whose spread cannot be contained. A spatially-explicit stochastic dynamic programming model is developed that tracks the state of each of N number of stands of a host tree species potentially infected by a damaging invasive species. Subject to the expected evolution of the forest, a manager is assumed to allocate (finite) resources to treat the forest, and can treat any stand in either a proactive (prior to arrival of the invasive) or reactive (after invasive establishment) manner. Results highlight the circumstances under which proactive management is favored, including the physical structure of the forest, stand/forest benefits, management costs, and the probabilities of pathogen spread.

We contribute to the literature in the following ways. First, to our knowledge, there are no published articles in the economics or forestry literature that utilize a dynamic programming methodology to evaluate forest management strategies in the presence of an invasive species. There are, however, a few examples of using these techniques for timber management, including Spring and Kennedy (2005), who examined optimal harvest on multiple stands in the presence of stochastic fire risk and an endangered species in Australia, and Moore and Conroy (2006), who examined silviculture practices for management of old growth forests for habitat purposes in a wildlife refuge in Georgia. Second, there is little in the economics literature regarding proactive management, perhaps because these strategies are contrary to current conservation approaches that would advocate preservation of native genotypes. However, proactive management may enable naturalization of the non-native organism while sustaining host populations and ecosystem function (Kilpatrick 2006). Finally, this study contributes to the literature on spatial process in the environmental and resource literature through the incorporation of an explicit spatial structure in the representation of the forest through which an invasive organism moves. In the presence of budget constraints, decisions regarding which stands to manage (either proactively or reactively) will inevitably involve tradeoffs over space as well as time.

2. Rationale of Proactive Management: The Case of White Pine Blister Rust (WPBR)

Cronartium ribicola, the fungus that causes WPBR, is among the invasive species introductions into North America where containment and eradication efforts have failed (Maloy 1997). It was introduced on the northeast cost of North America from Europe in the early twentieth century, and has since caused a variety of damage to the keystone species of noncommercial five-needle pines in high elevation North American ecosystems, including foxtail, limber, Rocky Mountain bristlecone, southwestern white, and whitebark pines. WPBR is a lethal disease that causes tree mortality at all life stages, disrupting the regeneration cycle with potentially severe effects on white pine forests.[2]

Damages as a result of WPBR infection and tree mortality include effects on various ecosystem components and services such as animal populations (such as Clark's nutcracker birds, grizzly bears, and red squirrels), watershed production through snow capture, biodiversity and degradation of high-quality recreation opportunities (Petit, 2007; Samman et al. 2003; (Tomback and Kendell 2001; Tomback et al. 1995; Mattson 1992; McKinney 2004; Kendell and Arno 1990; McDonald and Hoff 2001). In fact, forests of these types are among the most visited

[2] Some infected areas in the American west have seen mortality of up to 90%.

in the country, including those found in the Western region of the National Park system (e.g., Glacier, Yellowstone, and Rocky Mountain National Parks).

The nature of five-needle pine forests suggests that natural evolution of resistance to WBPR is unlikely without intervention[3], though some natural genetic resistance has been identified in some stands. As such, breeding programs may help to preserve naturally resistant seed stock in high-elevation species, as is being done for commercial species of white pines (McDonald et al. 2004). The potential may soon exist for proactive management in which genetically-resistant trees are either directly planted or indirectly encouraged through alternative management actions (stimulating natural regeneration of resistant trees) *prior to* infection (Schoettle 2004a, 2004b, Schoettle and Sniezko, 2007). The rationale behind proactive management, then, is essentially preventative. Acting prior to invasion would presumably limit mortality and impact on various ecosystem services, increase the probability of a healthy, regenerative system in the long run, and reduce or eliminate the need for reactive management post-invasion. Of course, such management might also be not only directly costly (through management expenditures), but also generate costs (to, say, recreationalists or naturalists) from the disturbance of a previously undisturbed forest. We term such costs “management externalities”.

To date, there has been little information provided to potential forest managers regarding the circumstances under which proactive management might be preferred to the more common reactive strategies (Burns et al. 2008). In the following sections, we provide a preliminary model that helps to shed light on these issues. Future research will refine the model using data on non-

[3] Individuals within these species can live for 1,000-4,500 years, can thrive in harsh environments, and are not frequently disturbed through stochastic events such as fire (Schoettle 1994; Schoettle and Rochelle 2000; Schauer et al. 2001; Schulman 1958; Curry 1965; Brustein and Yamaguchi 1992).

market benefits of high-elevation forests and the epidemiology of WPBR in the Rocky Mountain region.

3. Model

3.1 General Description of the Dynamic Management Model

We assume that a resource manager has responsibility over a forest threatened by a non-native species whose spread cannot be arrested through any management action (a circumstance such as WPBR). As in Spring and Kennedy (2005), the forest is composed of N stands, with the state of each stand in time period t represented by one of a countable number of states representing a) the health of the stand (or level of ecosystem services provided by the stand) and b) the status of the stand as “treated” or “untreated”. An untreated stand, once infected by the invasive pest and left untreated, will dynamically evolve such that mortality increases (ecosystem services decrease) until a terminal level is reached and maintained throughout the infinite time horizon of the problem. Once treated, a stand recovers until it reaches a relatively healthy terminal state, where it remains for the remainder of the problem.

The manager may treat any stand at any time, but is subject to a budget constraint that limits the number of stands treated in any one decision period. For simplicity, we assume only one treatment alternative whose success is certain (though this is fairly easily relaxed), and per-stand treatment costs are assumed to decrease with tree mortality (increase with ecosystem service provision). As noted above, spread of the invasive species is assumed not to depend on management actions, and is directional and potentially probabilistic in its spread. Ecosystem service benefits from the physical state of each stand are assumed to be homogeneous and decreasing in stand mortality, and total net benefits from the forest are additive across stands. The manager is assumed to maximize the net present value of the expected net benefits from stand treatment over an infinite time horizon, subject to the spread and damage caused by the invasive species and the budget constraint.

3.2 Forest Dynamics

The model of the forest is cellular and spatial in nature, with N=4 stands. At any time t, each stand x_i, $i=1,\ldots,N$, is assumed to be in one of S=7 discrete states representing the overall health of the stand and the treatment status of it. Overall, there are three health states corresponding to ecosystem service provision (healthy, moderately healthy, and not healthy) and two treatment states (treated and untreated) for stands that have been infected by the invasive, plus one more state representing a healthy stand that has not yet been exposed to the non-native pathogen. The total number of potential states of the forest is thus $S^N = 7^4 = 2,401$, which illustrates the necessity of restricting attention to four stands using standard discrete-space numeric dynamic programming techniques.[4]

The states of each stand are defined categorically, where $x_i = 0$ implies lack of invasive establishment on an untreated stand. Let τ_i be an indicator variable that signifies if stand i has ever been treated, and restrict attention to stands where the invasive has been established. As such, untreated stands can take on states

$$x_i = \begin{cases} 1 \text{ if } \tau_i = 0 \text{ and stand } i \text{ is healthy} \\ 2 \text{ if } \tau_i = 0 \text{ and stand } i \text{ is moderately healthy} \\ 3 \text{ if } \tau_i = 0 \text{ and stand } i \text{ not healthy} \end{cases}. \tag{1}$$

Once treatment has occurred, the three potential states are

$$x_i = \begin{cases} 4 \text{ if } \tau_i = 1 \text{ and stand } i \text{ is healthy} \\ 5 \text{ if } \tau_i = 1 \text{ and stand } i \text{ is moderately healthy} \\ 6 \text{ if } \tau_i = 1 \text{ and stand } i \text{ not healthy} \end{cases}. \tag{2}$$

[4] For larger state spaces, more advanced techniques (rollout strategies, temporal difference learning, etc…) can be used to approximate the optimal solution. See, e.g., Bertsekas and Tsitsiklis (1996).

State transitions in time t+1 depend on the initial state of the stand at time t (namely x_{it}), the value of the treatment control variable for that stand ($u_{it} = 1 \text{ if treated}$), and in the case of an uninfected stand, the event of stand infection and establishment, denoted by the event indicator $\phi_i = 1$. The state transitions are thus defined as

$$x_{it+1}(x_{it},\phi_{it},u_{it}) = \begin{cases} 0 \text{ if } x_{it} = 0 \text{ and } \phi_{it} = 0 \text{ and } u_{it} = 0 \\ 1 \text{ if } x_{it} = 0 \text{ and } \phi_{it} = 1 \text{ and } u_{it} = 0 \\ 4 \text{ if } x_{it} = 0 \text{ and } \phi_{it} = 1 \text{ and } u_{it} = 1 \\ x_{it}\text{+1 if } 0\text{<}x_{it} < 3 \text{ and } u_{it} = 0 \\ x_{it}\text{+4 if } 0 \leq x_{it} < 3 \text{ and } u_{it} = 1 \\ x_{it}\text{-1if } 4 < x_{it} \leq 6 \\ 3 \text{ if } x_{it} = 3 \text{ and } u_{it} = 0 \\ 6 \text{ if } x_{it} = 3 \text{ and } u_{it} = 1 \\ 4 \text{ if } x_{it} = 4 \end{cases}. \quad \textbf{(3)}$$

Note that state 3 (unhealthy stand) is a terminal state for untreated regions, while state 4 (healthy stand) is a terminal state for treated regions. Assuming that the effects of treatment are certain and there are no other exogenous threats to the forest (e.g., fire, climate change, etc…), the only stochastic element in the model is the infection and establishment event $\phi_{it} = 1$. We turn to considerations of this variable in the next subsection.

3.3 Probabilities of Stand Infection and Spatial Forest Structure

The spatial configuration of the forest is represented by a NxN matrix $\mathbf{z}$, with elements $z_{ij} = (0,1)$. For row i, a non-zero element in position j indicates that an infected neighbor j increases the probability of infection of stand i in the following period. Similarly, for column j, a non-zero element in row i indicates that stand i is more at risk once j is infected. As such, through specification of this matrix, a "directionality" of spread can be modeled. For example, suppose that spread is deterministic in a southeast direction (including due east and due south), in the sense that once a neighbor to the north or west of stand *i* is infected in time *t*, then stand *i* will become infected in time *t*+1 with a probability of one, and otherwise will not be infected. Further assume that are stands arranged in a rectangular formulation such that stand 1 is to the northwest, stand 2 is northeast, stand 3 is in the southwest, and stand 4 is in the southeast. The matrix **z** is thus defined as

$$\mathbf{z} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \end{bmatrix}, \tag{4}$$

so that, for example, stand 4 will be infected in *t*+1 if any of stands 1, 2, or 3 are infected in time *t* (row 4), but the infection status of stand 2 only affects the probabilities associated with stand 4 (2nd column).

In general, we assume that the probabilities associated with establishment of the invasive on a given stand are a function of the number of infected neighboring stands as defined by the matrix $\mathbf{z}$. Let $s_{ij} = 1$ if $x_j > 0$, 0 otherwise, and define the number of infected neighboring stands for stand *i* as $\overline{n}_i = \sum_j z_{ij} \cdot s_{ij}$, with $0 \leq \overline{n}_i \leq 3$. The infection and establishment event, then, is a function of the spatial structure of the forest and the states of the surrounding stand, and the associated probabilities, namely $\Pr\left(\phi_i \mid \overline{n}_i(\mathbf{x}, \mathbf{z})\right)$, are given in Table 1.

Using these, define $\Pr\left(x_{ij}^{+} \mid x_i, \overline{n}_i(\mathbf{x}, \mathbf{z}), u_i\right)$ to be the probability of a stand transitioning from state x_i to state x_{ij}^{+} conditional on the state of the forest and the control chosen. Of the S^N potential states in the model, then, the transitions associated with $(S-1)^N$ are deterministic. In the case presented here, this is approximately 54% of all possible starting states in the stochastic model used in section 4.2.

3.4 Economic Parameters

Table 2 reports information about the benefits and costs associated with forest management. We assume that in each (multi-year) period, benefits from the forest are the sum of stand-level ecosystem service benefits, which are increasing with the health of each stand. We denote these as $f(x_i)$. Treatment costs $c(u_i, x_i)$ are incurred only in the current period, and are decreasing with the health of each stand due to ease of management and the potential for management externalities.

The manager is assumed to be constrained in action due to budget, and as such can only treat a limited number of stands per period.[5] As such, the control set U is defined directly from this constraint. For example, if the budget is one stand per year, then the number of elements in U is five, corresponding to treating each individual stand plus not treating any. If, however, two stands may be treated in the same time period, then the control set is augmented to include eleven possible stand combinations.

Collecting these assumptions and placing them in the framework of a dynamic programming problem, the discrete-time Bellman equation characterizing the problem is

$$\begin{aligned} V(\mathbf{x}) &= \max_{\mathbf{u}\in U}\left\{ \sum_i \left[f(x_i) - c(u_i, x_i)\right] + \beta E\left[V\left(\mathbf{x}^+(\mathbf{x}, \boldsymbol{\varphi}, \mathbf{u})\right)\right] \right\} \\ &= \max_{\mathbf{u}\in U}\left\{ \sum_i \left[f(x_i) - c(u_i, x_i)\right] + \beta \sum_{j=1}^{S^N}\left[\Pr\left(\mathbf{x}_j^+ \mid \mathbf{x}, \bar{\mathbf{n}}(\mathbf{x},\mathbf{z}), \mathbf{u}\right) V\left(\mathbf{x}_j^+(\mathbf{x}, \boldsymbol{\varphi}, \mathbf{u})\right)\right] \right\}, \end{aligned} \tag{5}$$

where $\mathbf{x}^+(\mathbf{x}, \boldsymbol{\varphi}, \mathbf{u})$ is the vector of state transition equations defined in (3), $\Pr\left(\mathbf{x}_j^+ \mid \mathbf{x}, \bar{\mathbf{n}}(\mathbf{x},\mathbf{z}), \mathbf{u}\right)$ is the probability of transition from state $\mathbf{x}$ to $\mathbf{x}_j^+$, defined as the product of the stand level probabilities $\Pr\left(x_{ij}^+ \mid x_i, \bar{n}_i(\mathbf{x},\mathbf{z}), u_i\right)$, and β is the discount factor, suitably defined to reflect the number of years assumed between each time period.

[5] Given this assumption, the interpretation of the budget constraint should not be strictly monetary. Rather, one might interpret it as a binding constraint on additional resources, such as labor or capital.

The model was coded and solved numerically in MATLAB using the default policy iteration method of the CompEcon toolbox in Miranda and Fackler (2002).

4. Results

4.1 Optimal Deterministic Policies

Optimal policies for a sample of starting states under two budget constraints (a maximum of one stand treated per decision period and a maximum of two stands treated per decision period) are presented in Table 3, assuming deterministic invasive species spread in the southeast direction with stands one and two to the north and stands three and four to the south arranged in a rectangular fashion (see Figure 1). The discount factor is assumed to be 0.9.

Under the baseline parameterization and considering the case of a maximum of one treated stand per period, there are 1,105 forest configurations in which proactive management, defined relatively strictly as treating an uninfected, previously untreated stand, is feasible.[6] Of this set, approximately 13% (145) of the optimal management strategies could be classified as proactive. The large majority of these occur when the infection threat is immediate (i.e., a stand to the northwest of an uninfected stand is infected), and the other infected stands are either uninfected, or have already been treated, and thus are in states 4-6. Intuitively, this makes sense as the opportunity costs of treating a stand proactively in this case are small, given that the remainder of the forest is relatively protected and increasing in health.

If, however, at least one stand is actively degrading or degraded (states 1-3), it is generally optimal to treat one of these stands in a reactive fashion (though the specifics depend on the relative states of each degrading stand and the potential for damage through spread). One exception to this prescription is if exactly one of the stands is only moderately healthy (state = 2)

[6] Given the state transition structure assumed here, it might be logical to term treatment of infected, healthy stands (state 1) as proactive. We choose not to in order to shed light on primarily "preventative" management options, rather than "quick response" actions implied by treatment of infected, healthy stands.

and the only other infected stand has been treated. In this case, the optimal strategy is to proactively treat the northeast-most uninfected stand. Presumably, this result occurs as a result of the interaction between the opportunity costs of treatment and the fact that treatment costs for the moderately infected stand will fall enough such that it pays to wait to treat. We further explain the incentives in section 4.2 below.

If the budget constraint is relaxed to accommodate treatment of up to two stands per time period, then the percentage of times it is optimal to pursue proactive strategies increases to 41%, more than three times the one-stand per time period number. This set of proactive strategies generally includes cases where if there are two or more stands infected, at least one has already been treated. Given the flexibility inherent in this parameterization of the problem, the spatial dimension is more apparent as well. For example, a manager will generally treat degrading cells to the northwest, ceteris paribus, through s/he still must trade off the potential for spread and increased future damage with the cost decrease (and own-stand damage increase) if treatment does not occur.

As such, we conclude that proactive management under this deterministic directional spread scenario is generally favored as resource constraints are relaxed, but not at the expense of reactive management when multiple stands are degrading. However, this is but one set of benefit and cost schedules, suggesting an analysis of the effects of these measures at the margin is appropriate.

4.2 The Effects of Benefits and Costs

Of course, the tradeoffs involved in dynamic forest management in the presence of an invasive species are in large part determined by the marginal benefits and costs of treatment, which in turn depend on both spatial and temporal features. We now turn to the effects of shifting the relative benefit and cost schedules associated with forest stands in order to determine their effects.

To illustrate, we run an experiment which doubles the cost of treatment in healthy stands and cuts the cost of treatment in unhealthy stands by half, while keeping costs for the moderately healthy stands the same in the two-stand constrained deterministic spread model. Thus, we have increased the marginal costs of treating a healthy forest, perhaps mirroring a case of relatively severe management externalities.

Following our earlier analysis, proactive strategies are now optimal for almost 57% (626/1105) of possible cases, despite the increase in treatment costs for uninfected and healthy stands. Part of the reason can be seen in from the difference in strategies when $\mathbf{x}_a = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}'$ and $\mathbf{x}_b = \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix}'$. When the cost of treatment for healthy stands is relatively low, $u_a^{low} = \left[treat\ 1 \& 2 \right]$, but when it is relatively high, $u_a^{high} = \left[treat\ 2 \& 3 \right]$. Similarly, for $\mathbf{x}_b$, $u_a^{low} = \left[treat\ 1 \& 2 \right]$ and $u_a^{high} = \left[treat\ 3 \& 4 \right]$. Note that in case *a*, both scenarios involve proactive management, while in case *b*, only u_a^{high} treats (both) uninfected stands.

This result cannot simply be explained by a change in the relative costs across cells, as treatment costs are homogeneous across all four stands. As such, the answer must lie with the opportunity costs of treatment. Advancing the system in case a) according to the optimal policy, $\mathbf{x}_a^{+low} = \begin{bmatrix} 5 & 4 & 1 & 1 \end{bmatrix}'$ and $\mathbf{x}_a^{+high} = \begin{bmatrix} 2 & 4 & 4 & 1 \end{bmatrix}'$, with corresponding policies at these new states defined by $u_a^{+low} = \left[treat\ 3 \& 4 \right]$ and $u_a^{+high} = \left[treat\ 1 \& 4 \right]$. Following the paths to their terminal states of $\mathbf{x}^{\infty} = \begin{bmatrix} 4 & 4 & 4 & 4 \end{bmatrix}'$, as in Table 4, it is clear that the *low* takes three decision periods to reach $\mathbf{x}^{\infty}$, while the *high* case takes four. The reason is that in the *high* case, the marginal benefit from the treatment cost reduction outweighs the (discounted) marginal reduction in benefits from allowing stand 1 to devolve into an unhealthy state, and then recovering once treated. Thus, the manager prefers what we might call a "purely" proactive strategy in period one, but does so, perhaps counter intuitively, in order to capture the "benefits" of stand degradation.

Turning to case *b*, we see a very similar result, as the manager prefers to engage in a proactive strategy to protect stands 3 and 4 in the first period, while allowing for stands 1 and 2 to degrade in order to take advantage of the relative cost savings offered by treating partially healthy forests. These savings dominate the decision despite the additional expense of loosing benefits in period two (after the second control decision), relative to the *low* case, as a result of two unhealthy treated stands that take an extra period to return to health.

We have thus illustrated that proactive strategies tend to be favored when the costs of stand treatment are increasing relatively rapidly in stand health, and conversely, then, when the benefits of stand health are relatively unresponsive to degradation. Given the role that future damages play in the analysis, however, we now turn to the effect of the discount rate on the solution to the problem.

4.3 The Effect of the Discount Rate

The baseline analysis assumed a discount factor of $\beta = 0.9$ as weights between the (unspecified) time period between which decisions regarding treatment are made and the forest stands evolve. Without greater biological detail, it is hard to determine if such a weighting is appropriate for all scenarios. On the one hand, the length of time it takes species such as five-needle pines to grow and evolve might suggest that the discount factor should be lower; on the other hand, intergenerational equity and other concerns provide an argument that the discount factor should be relatively close to one (Spring and Kennedy, 2005; Weitzman 2001).

In order to investigate the effects of the discount rate, additional scenarios were analyzed as the discount factor decreased (less weight on the future). One would suspect that as the present was favored, the incentives for proactive management would decrease as the marginal benefits of treating an individual stand would decrease. In fact, this is exactly the case, and in some cases, is quite dramatic. For example, if the discount factor is 0.5 under the two-stand constraint, then the optimal strategy is to treat only completely degraded stands once that state is reached, and do nothing to any other stand in any other state. As such, the percentage of potential proactive management occasions that are optimal is zero. At $\beta = 0.65$, this percentage increases to a very small one half of one percent (all cases where stand 1, which is positioned to spread the invasive to all other stands, is infected), and when $\beta = 0.70$ and higher, the result is identical to the baseline scenario.

As such, so long as the discount rate (factor) is sufficiently low (high), proactive management strategies are part of the optimal forest management plan. In the cases considered here, there is a fairly narrow range with $.60 < \beta < .70$ over which the optimal policies are affected, and tend to favor proactive strategies only when the spread potential for the invasive species is high and the forest is generally healthy. This corresponds to a situation in which a low weight placed on future outcomes is outweighed by the damage caused from increased invasive spread.

4.4 The Effects of Uncertainty

In addition to the deterministic scenarios analyzed above, the model was also solved taking into account a probabilistic establishment regime for the invasive (see Table 1), but maintaining all other baseline scenario parameters for the two-stand constrained problem. In general, this scenario assumes that the threat of the invasive to an uninfected stand is increasing in the number of infected stands that have the ability to threaten it (in the sense of the matrix **z)**. In addition, there is an external threat in that the forest in the state [0 0 0 0] can become infected (in this case, with a probability of .4). For simplicity, the manager is assumed to maximize the expected net present value of profits, and thus is risk neutral in preferences.

Results of this exercise reveal that only small changes in optimal policy rules occur as a result of the uncertainty over spread.[7] In each case, it involves two infected stands with one treated, but the other two are undisturbed and must include stand 4. As direct result of the differential in probabilities of potential spread between the two stands, it is always optimal in the stochastic case to treat the "more threatened" stand 4, primarily as a direct result of the differential in probabilities of potential spread between the two stands. In the deterministic case, given the **z** matrix, the manager is indifferent between which stands to treat, as the probabilities related to spread are identical. As a result, there is no effect in the frequency of optimal proactive management over the deterministic case; rather, this result serves to guide the choice of stands to proactively manage, if there is indeed such a choice.

5. Discussion and Conclusions

This paper offers a preliminary investigation into the conditions under which it might be optimal to engage in proactive management of a non-timber forest resource in the presence of an invasive species whose spread is unaffected by management action. Although contrary to current practice, proactive management is defined as treating an uninfected area in order to encourage healthy ecosystem function, given that the arrival of the invasive is inevitable. The model is inspired by the problem of white pine blister rust (WPBR) in the Rocky Mountain west of the United States,

[7] Of course, we expect no difference in policy rules where proactive management is not possible, as these transitions are deterministic by assumption.

which has severely impacted Glacier National Park, and is currently threatening Yellowstone and Rocky Mountain National Park, among other public lands.

The model was solved under varying assumptions concerning the potential scale of management action (through the budget constraint), the benefit and cost schedules associated with the forest resource, the discount rate, and the level of uncertainty of spread. Results showed that proactive management strategies tended to be optimal when, ceteris paribus, a) more resources are available for treatment (i.e., a greater number of stands can be treated in any one decision period); b) the costs of treatment are rapidly increasing in forest health, or conversely, the benefits of healthy and unhealthy stands are relatively similar; and c) the discount factor (rate) is high (low), implying a relatively high weight on the future. Additionally, although the introduction of uncertainty did not significantly affect the likelihood of a proactive management strategy being optimal, it did show that the conditional probabilities of infection play important role in the decision of which uninfected stand should be treated if a choice is available to the manager.

Although relatively simple, the model presented here should help managers understand the incentives related to non-timber forest management in the presence of an unavoidable and unalterable threat from an invasive species. That said, future research can do much to clarify and augment the conclusions reported here. For example, improved parameterizations for a given circumstance, including the economic and biological/epidemiological representations of the system based on collected data, could assuage concerns about arbitrary assumptions. This includes not only state-space representation of the forest, but the number of potential management units as well. Similarly, managers have multiple treatment strategies available (planting, burning, both, etc…), with outcomes of any strategy likely uncertain, with potentially varying streams of benefits and costs over time. As the modeling effort becomes more complex and thus more reflective of the system it represents, the results presented here can be used to verify and validate future results, as well as help inform about other similar processes and problems, such as the spread of infectious disease.

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Table 1: Stand infection probabilities as a function of number of infected neighbors, deterministic and stochastic cases

# of infected neighboring stands ($\bar{n}_i$)	$\Pr\left(\phi_i \mid \bar{n}_i(\mathbf{x},\mathbf{z})\right)$ Deterministic	Stochastic
0	0.0	0.1
1	1.0	0.6
2	1.0	0.8
3	1.0	0.9

Table 2: Net present value of benefits and costs for forest stand states per time period, baseline scenario

State of stand x_i	Description	Per-stand benefits $f(x_i)$	Per-stand treatment costs $c(u_i, x_i)$
	Uninfected and not established		
0	Uninfected, healthy	10	7
	Infected and established		
1	Infected and healthy	10	7
2	Infected and moderately healthy	5	5
3	Infected and not healthy	0	2
4	Treated and healthy	10	7
5	Treated and moderately healthy	5	5
6	Treated and not healthy	0	2

Table 3: Optimal policies for selected starting states and budget constraints, deterministic model

Starting States				Optimal Treated Stands and Proactive Indicator: max 1 treated		max 2 treated	
Stand 1	**Stand 2**	**Stand 3**	**Stand 4**	**Treated Stand**	**Proactive?**	**Treated Stands**	**Proactive?**
0	0	0	0	none	no	none	no
1	0	0	0	1	no	1,2	yes
1	1	0	0	1	no	1,2	no
1	4	0	0	1	no	1,3	yes
2	0	0	0	2	yes	1,2	yes
2	4	4	1	3	n/a	3,4	n/a
5	4	4	1	4	n/a	4	n/a
6	4	4	5	none	n/a	none	n/a
4	4	4	4	none	n/a	none	n/a

Table 4: Sample simulations under alterative treatment cost assumptions, deterministic, two-stand constraint model

	Case *a*											
	Low Cost Scenario				High Cost Scenario				High Cost Scenario Using Low-Cost Policy			
Time Period	Forest State	Treated Stands	Benefits - Costs	NPV	Forest State	Treated Stands	Benefits - Costs	NPV	Forest State	Treated Stands	Benefits - Costs	NPV
0	[1 0 0 0]	1,2	26	26.00	[1 0 0 0]	2,3	12	12.00	[1 0 0 0]	1,2	12	12.00
1	[5 4 1 1]	3,4	21	18.90	[2 4 4 1]	1,4	16	14.40	[5 4 1 1]	3,4	7	6.30
2	[4 4 5 5]	n/a	30	24.30	[6 4 4 5]	n/a	25	20.25	[4 4 5 5]	n/a	30	24.30
3	[4 4 4 4]	n/a	40	29.16	[5 4 4 4]	n/a	35	25.52	[4 4 4 4]	n/a	40	29.16
4	[4 4 4 4]	n/a	40	26.24	[4 4 4 4]	n/a	40	26.24	[4 4 4 4]	n/a	40	26.24
			Total	124.60			Total	98.41			Total	98.00
	Case *b*											
	Low Cost Scenario				High Cost Scenario				High Cost Scenario Using Low-Cost Policy			
0	[1 1 0 0]	1,2	26	26.00	[1 1 0 0]	3,4	12	12.00	[1 1 0 0]	1,2	12	12.00
1	[5 5 1 1]	3,4	16	14.40	[2 2 4 4]	1,2	20	18.00	[5 5 1 1]	3,4	2	1.80
2	[4 4 5 5]	n/a	30	24.30	[6 6 4 4]	n/a	20	16.20	[4 4 5 5]	n/a	30	24.30
3	[4 4 4 4]	n/a	40	29.16	[5 5 4 4]	n/a	30	21.87	[4 4 4 4]	n/a	40	29.16
4	[4 4 4 4]	n/a	40	26.24	[4 4 4 4]	n/a	40	26.24	[4 4 4 4]	n/a	40	26.24
			Total	120.10			Total	94.31			Total	93.50

Low cost scenario: Treatment costs = $7 for healthy, $5 for moderately healthy, $2 for unhealthy
High cost scenario: Treatment costs = $14 for healthy, $5 for moderately healthy, $1 for unhealthy
Discount factor = 0.90

Figure 1: Spatial configuration and predominant direction of spread (arrows) of a sample forest