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METHODS

Optimal detection and control strategies for invasive species management

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ABSTRACT

The increasing economic and environmental losses caused by non-native invasive species amplify the value of identifying and implementing optimal management options to prevent, detect, and control invasive species. Previous literature has focused largely on preventing introductions of invasive species and post-detection control activities; few have addressed the role of detection. By increasing resources to detect invasive species, managers may increase their chances of finding a species at a smaller population level, lessening the extent of damages and making subsequent control potentially less expensive and more effective. However, detecting new invasive species is difficult and uncertain; many factors reduce the likelihood of successful detection, such as low population densities which are prevalent in invasive species management. This paper presents a model that captures the stochastic and dynamic aspects of this trade-off by incorporating a detection stage in which the agency managers choose search effort prior to the post-detection control stage. The analysis of the model illustrates that the optimal detection strategy depends primarily on the 'detectability', or ease of detection, and the biological relationships of each distinct species.

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1. Introduction

Non-native invasive species (NIS) cause major environmental damages (Wilson, 1992) and substantial economic losses (OTA, 1993). Certain highly successful invaders, such as the gypsy moth (*Lymantria dispar*), have produced significant damages, while many others, such as the Asian longhorned beetle (*Anoplophora glabripennis*), present imminent risk (Wallner, 1997; Novak et al., 2001). As trade and travel increase worldwide, the number of NIS introductions continues to rise (Perrings et al., 2002). Ecosystems may become more vulnerable through disturbance from human activity or the spread of other invasive species. These issues, along with limited resources available to government agencies charged with controlling invasive species, mean that there is significant value in identifying and implementing optimal management strategies while accounting for the salient ecological and economic factors affecting invaders.

In order to avoid damages, much of the previous literature has focused on preventing introductions believing that "the best offense is a good defense". The argument for focusing on preventing introductions is that once the species has been

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introduced, controlling the species can be very expensive and may be impossible. However, species enter through numerous pathways, such as commodity and human movement. Screening a large number of potential pathways and carriers is an enormous and costly task. Additionally, the probability that an introduced species will actually become an invader is slim (Williamson, 1996).

Rather than focusing exclusively on preventing introductions, optimal non-native invasive species policy involves a combination of strategies such as efforts to detect new invasive species, and activities to monitor and control existing populations of invasive species. If an incipient invasive species population is detected before it establishes and spreads, subsequent control costs may be low and eradication can be a viable option. However, the costs associated with detecting a nascent invasive species, especially at low population levels, may be quite high. Detection of new invasive species at low population levels is often difficult unless they produce highly visible damages.

In this paper, we analyze the trade-offs between detection and subsequent control costs using a stochastic dynamic model for a single invasive species. Unlike the prior literature, our model focuses on the detection stage when the agency manager determines the level of search effort to detect an invasive species. The manager identifies the optimal search effort by minimizing the expected present value of the total costs of search plus controlling the population. We apply the model to identify the optimal search intensity for species with different economic and biological characteristics.

This paper contributes to the invasive species literature by formally modeling the detection decision and analyzing potential trade-offs between allocating resources to detection versus post-detection control costs. Section 2 provides a brief background of current policies and literature and the need for the explicit analysis of detection. Section 3 presents a simple model and uses simulations to represent four distinct invasive species that differ in their biological and economic characteristics. This model is a first step towards fully incorporating the detection stage in developing optimal invasive species policy. Section 4 discusses the findings and suggestions for future research.

2. Invasive species management: extant policies and literature

The severity of past biological invasions, such as the gypsy moth, or impending invasions, such as the soybean pod borer (*Leguminivora glycinivorella*), have prompted increased efforts by the United States Department of Agriculture (USDA) to attenuate the risk of introductions and spread of additional species. In 2006, the federal government will spend approximately $1.3 billion on invasive species management which is 60% higher than the funding in 2002 (NISC Fact Sheet FY, 2006). The management activities of prevention, detection and control roughly coincide with each phase of the invasion process: introduction, establishment, and spread. Approximately 20% of federal invasive species' funding in the U.S. is earmarked for early detection and rapid response activities while control activities consume roughly 37% of the total funding (NISC Fact Sheet FY, 2006).

Prior economic literature has analyzed the effects of various aspects of invasive species management vis-à-vis current policies and initiatives. Much of this literature centers on the introduction stage where management consists of inspections to prevent the arrival of unwanted species. Since this paper emphasizes the detection stage that follows the introduction stage, it is essential to understand how this model of detection is distinct from existing models that focus on prevention. Both prevention and detection entail monitoring activities. Prevention, however, relies on monitoring to exclude species from entering an ecosystem, thereby eliminating the need for control strategies. Monitoring as a detection strategy works in tandem with control strategies to find species that have already entered an ecosystem and to allow for quicker implementation of control measures.

Unintentional NIS introductions are closely linked to human movement, namely travel and trade. Numerous papers discuss this relationship (e.g., Jenkins, 1999; Dalmazzonne, 2000; Costello and McAusland, 2003; McAusland and Costello, 2004; Costello et al., 2005; Knowler and Barbier, 2005; Margolis et al., 2005) and assess various policy mechanisms, primarily market-based instruments such as tariffs, to reduce introductions. Some of these papers explicitly deal with uncertainty during the introduction stage by modeling the stochastic processes governing species' introductions (Costello et al., 2005). While many analysts claim that the rate of introductions is increasing over time (e.g. Perrings et al., 2002), Costello and Solow (2003) argue that this may not be the case. There is often a substantial time lag between introduction and detection. As species populations expand it becomes more likely that they will be detected. A high current rate of detection may indicate a high rate of current introductions, or alternatively, that past introductions have established and spread to the point where they are more easily detectable.

Prevention activity often involves inspecting potential vectors, such as cargo, to intercept non-native species. Upon interception of a single actionable pest, the vector is treated, destroyed or returned to its country of origin. Although this is a common approach, technological (and political) limitations ultimately lessen the effectiveness of inspection as a preventative measure. Currently, the USDA inspects a maximum of 2% of all cargo at U.S. ports (Haack, 2001). Inspections are unlikely to detect non-native species unless they occur at high densities (Venette et al., 2002). Existing literature has examined the types of species being apprehended and the interception rates, yet the relationship between the interception rate during the introduction stage and the subsequent establishment of species remains unclear.

While the majority of the previous invasive species literature have focused upon single stages, several papers have analyzed the trade-offs between the prevention and control stages (e.g., Leung et al., 2002; Leung et al., 2005; Olson and Roy, 2005; Finnoff et al., in press). These papers commonly find that investing in prevention activities is optimal versus investing in control strategies. Models emphasizing prevention and control often apply data from 'catastrophic' invaders, e.g. gypsy moths or zebra mussels, which have explosive population growth. But these cases are not typical. Other species have long lag periods between introduction, establishment and spread (Crooks and Soulé, 1999) requiring models which allow for more than just the extreme cases where invaders progress quickly from introduction to spread.

Detection efforts comprise a considerable part of management actions. Some species, such as the black-striped mussel (*Mytilopsis* sp.) in Australia, have been eradicated due to constant surveying and quick mobilization after detection (Myers et al., 2000). Several papers have shown that eradication is viable for small or isolated populations (Sharov and Liebhold, 1998; Olson and Roy, 2002; Liebhold and Bascompte, 2003). Thus, early detection is essential for effective control and eradication. State-level government agencies, such as the Minnesota Department of Agriculture's (MDA) Invasive Species Unit, devote significant resources to detection. The MDA administers statewide surveys of over 50 crop pests under the Plant Pest Survey program. This program determines the distribution and density of known and potential species (MDA, Invasive Species Unit, Annual Report FY, 2005). Such surveys form an integral part of monitoring and detecting invasive species. Currently, government agencies decide how often and which pests to include in these surveys without explicitly incorporating economic information or relationships. In the sections that follow, we develop and analyze a model that incorporates the detection decision, along with the post-detection control decision, in an economic framework.

3. Detection and control

This section discusses the government agency's decision regarding allocation of resources to detection based on expected damages and the probability of detection. Section 3.1 describes the basic framework of the model, including several important simplifications that allow analytic solutions. Section 3.2 provides a numerical analysis for four scenarios representing different types of invasive species. Section 3.3 demonstrates the effects of uncertainty in initial population size. Section 3.4 analyzes the role of a growing population on the ease of detection.

3.1. *Detection framework*

Since early detection of a species contributes to the ability to control the population while it is still manageable, government agencies continually survey land to detect potentially invasive species. Surveys include species deemed potentially risky and species that have a greater chance of being present in that area. For example, the Emerald ash borer (*Agrilus planipennis*) has been detected in several states including Michigan, Ohio, Indiana, and recently in Illinois. An agency manager in Minnesota may believe that the probability of the Emerald ash borer entering Minnesota is now higher since several regional neighbors have been affected. In this case, the manager has a belief that a species can potentially enter an area but she has yet to detect it. Given her beliefs about the species, she must decide how many resources to allocate to search effort, represented by S. She selects the optimal search effort, S^*, based on the sum of the search costs, control costs and damages. If she devotes greater effort to search, her chances of finding the species at an earlier date will increase, assuming the species is present. Subsequently, she will be able to commence control activities sooner thereby reducing the sum of control costs and damages.

If the manager decides to engage in search activities, she will choose a constant level of search effort from the start of species management, $t=0$, which will continue until the pest is detected at time period $t=\tau$. Once the species is detected, she will switch her management activity from search to post-detection control. Her objective is to minimize the expected total costs of management and the damages caused by the species ($E[TC]$). The expected total costs consist of two parts: 1) the costs and damages during the detection stage and 2) the discounted present value of costs and damages during the post-detection control stage. In the detection stage, the manager faces the costs of search as well as the damages caused by the species. Let $G(S)$ represent the costs of search per unit of time during the detection stage:

$$\frac{\partial G(S)}{\partial S} > 0 \tag{1}$$

Search effort, S, corresponds to the number of man-hours spent searching for the specific species. Identifying a constant search effort, instead of a time-dependent search path, produces an analytically tractable solution that acts as a "rule-of-thumb" to broadly assess a situation. Also, under a general framework in which the probability of establishment is constant over time, it is reasonable to consider a model with constant search effort.

Assuming the species is present in the area, the species population, $x(t)>0$, grows according to a natural growth function, $F(x(t))$. The species causes damages, $D(x(t))$, which are increasing in the population size:

$$\frac{\partial D(x(t))}{\partial x(t)} \geq 0 \tag{2}$$

We assume the detection stage ends once the species is detected at $t=\tau$. Control begins immediately after the species is detected. This is similar to actions undertaken as part of the Federal government's Early Detection and Rapid Response initiative (NISC Fact Sheet FY, 2006). Once the species is detected, control activity commences immediately to reduce, and possibly eradicate, the species. These post-detection control efforts are represented by the discounted present value of control, $H(\tau)$. The discounted present value of control includes both the costs of reducing the species as well as the damages from the remaining population.

The time of detection, τ, depends on the search effort and its effectiveness. The likelihood of successful detection depends on several characteristics such as available technology or the visible damages that can be noticed during the surveys. The efficacy parameter, k, represents the effectiveness of the search effort which is the ability of the search to successfully detect species. The time of detection, τ, is distributed according to the probability distribution $q(\tau|S,k)$. The distribution function is continuous in S and k with:

$$\frac{\partial E[\tau]}{\partial S} < 0, \quad \frac{\partial E[\tau]}{\partial k} < 0 \tag{3}$$

The minimization problem for the expected total costs of search and control is given by:

$$E[TC] = \min_{S} \int_0^{\infty} \left[\left(\int_0^{\tau} e^{-rt} [G(S) + D(x(t))]\, dt \right) + e^{-r\tau} H(\tau) \right] \times q(\tau|S,k)\ d\tau \qquad (4)$$

$$\text{s.t.} \qquad \dot{x}(t) = F(x(t)) \qquad (5)$$

$$x(0) = x_0 \qquad (6)$$

where $r>0$ is the discount rate. The initial condition for the state Eq. (6) represents the initial population size at the start date of the management policy ($t=0$). We assume the initial population size, x_0, is known. Realistically, the manager cannot know the initial population size until the population is detected. Even then, she may not know the population size with certainty. This assumption is relaxed in Section 3.4.

The manager chooses the optimal search effort, S^*, which minimizes expected total costs. The choice of search intensity, S, depends on several factors: 1) the efficacy of search, which determines how search effort shifts the probability density function of the timing of detection, 2) the difference between damages pre-detection versus control and damage costs post-detection, 3) initial population size, and 4) the speed of population increase. The next section illustrates the properties of this model for four cases of invasive species.

3.2. *Numerical examples for four types of invasive species*

While 'catastrophic' invaders such as the gypsy moth and the Emerald ash borer garner much attention, agencies also spend time for lesser known invasive species, such as the small hive beetle (*Aethina tumida*) that affects honeybees. Previous papers tend to use data from major invasive species which makes sense since a great deal of data exists for these invaders due to the enormity of their damages. On the other hand, agencies deal with a wide range of invasive species, thus variegated species need to be included in the analysis to determine the range of optimal strategies. This section analyzes four cases of invasive species with distinct characteristics captured by varying parameters to illustrate how optimal management strategies differ.

The functional forms for the relationships in the model are assumed to be the same for all four cases. Search effort consists of experts and volunteers surveying forest or cropland with visual inspections and traps. The costs of the search effort are assumed to be convex and increasing in search effort:

$$G(S) = bS^2 \qquad b>0,\ S>0 \qquad (7)$$

Convex costs of search effort, or increasing marginal costs, can arise for many reasons such as overtime pay for increased surveying or additional training for new hires.

Species inflict greater damage as the population size grows. The damages caused by the population are assumed to be convex and increasing in the population size, $x(t)$:

$$D(x(t)) = p\,x(t)^2 \qquad p>0,\ x(t)>0 \qquad (8)$$

While the populations are small, the species are often dispersed. As the populations grow, the concentrations in certain areas increase, leading to increasing marginal damages.

The population is assumed to grow according to an exponential growth function where the species' intrinsic growth rate is represented by a, a strictly positive parameter:

$$\dot{x} = F(x) = ax \qquad a>0, \quad x(0) = x_0 \geq 0 \qquad (9)$$

This model is primarily concerned with the initial stage of population establishment and spread. During this initial period, population growth is well approximated by exponential growth. The initial population size at $t=0$, x_0, is assumed to be known. In reality, the initial population size will not be known. We will relax this assumption in Section 3.4.

The present value of post-detection management, $H(\tau)$, is a continuous, increasing function of the population at the time of detection $x(\tau)$:

$$H(\tau) = cx(\tau)^2 = c(x_0 e^{a\tau})^2 \qquad c>0 \qquad (10)$$

The present value of management subsumes the damages from the remaining species and the removal costs of controlling the species to represent the costs in the post-detection control stage. As control efforts lessen the species population, the resulting damages from the species also decrease. The decision to detect and remove depends on the relative costs of the control method and the reduction in damages as a result of the control method (i.e. the benefits of implementing control measures). We assume this function represents an optimal pre-determined control strategy based on the population size upon detection at $t=\tau$.

By minimizing the total costs in the detection and control stages, the manager can find the optimal search effort. While the time of detection is not known, it is governed by a probability distribution which is a function of search effort and the detection parameter, k, which denotes the efficacy of search. We assume the probability distribution function is an exponential function of S and k. This function is only well-defined for positive values of S and k. In the limit as search effort goes to zero, the time to finding the invasive species goes to infinity. In this case, the expected total costs are equal to the present value of damages. With an exponential distribution the constant search effort and the constant efficacy parameter result in a constant detection rate:

$$q(\tau|S,k) = kSe^{-kS\tau} \qquad S>0, k>0 \qquad (11)$$

The exponential probability distribution has a "memory-less" property, which means that the probability of detection does not depend on previous periods. The expected time of detection is decreasing in both the efficacy parameter and the search effort. We assume a constant detection parameter but relax this assumption in Section 3.4.

Substituting these functional forms into Eq. (4) and integrating produces the manager's discounted expected total costs of detection and control:

$$E[TC] = \min_{s} \left\{ \frac{bS^2}{r+kS} + \frac{(p+ckS)x_0^2}{r+kS-2a} \right\} \qquad (12)$$

We assume that $r>2a$. For this solution to converge as $t\rightarrow\infty$, the assumptions that $r>2a$ and that the parameters r, a, and k

and the variable S are strictly positive, must hold. The assumption that $r>2a$ highlights a key feature of this model. The assumption states that the manager discounts future periods at a sufficiently high rate relative to the growth rate. This assumption guarantees that the present value of costs will decline through time, thus ensuring convergence on the integral shown in Eq. (4).

Differentiating the expected total costs with respect to the search effort yields the first- and second-order conditions:

$$\frac{\partial E[TC]}{\partial S} = \frac{bS(2r+kS)}{(r+kS)^2} - \frac{(2ac+p-cr)kx_0^2}{(r+kS-2a)^2} = 0 \tag{13}$$

$$\frac{\partial^2 E[TC]}{\partial S^2} = 2\left[\frac{br^2}{(r+kS)^3} + \frac{(2ac+p-cr)k^2x_0^2}{(r+kS-2a)^3}\right] > 0 \tag{14}$$

The optimal search effort, S^*, must satisfy these conditions. For the first-order condition (Eq. (13)) to hold for an interior solution of S^* ($S^*>0$), the parameters much satisfy the assumption

$$2ac + p - cr > 0 \Rightarrow r - 2a < \frac{p}{c} \tag{15}$$

Since $r-2a$ is assumed to be strictly positive, Eq. (15) indicates that the ratio between the damages during the detection stage, p, and the total costs and damages during post-detection control, c, must be sufficiently large. For detection to be a worthwhile endeavor, the post-detection control strategy must be such that the combined costs of control and the decreased damages resulting from the control, c, are relatively smaller than the damages of the uncontrolled population, p. For example, if the control costs for a species are very high relative to the species' damages ($c>p$), the manager will be better-off not taking any action and allowing the population to grow uncontrolled. While detection activities can allow control activities to begin at an earlier date, the present discounted value of those control activities must be reasonably cost-efficient. This characteristic has often been neglected in previous literature evaluating resource allocation between diverse management activities (Leung et al., 2002).

The relationships between the biological and economic parameters in the optimal solution are complex. In lieu of comparative statics, we use numerical simulations to delineate the model's properties and the sensitivity of outcomes to changes in parameters. Due to the paucity of adequate empirical data, illustrative values are used for the four cases (Table 1). We assume the search costs, b, are the same for all species. The costs of the pre-determined control strategy, c, vary for the four species since the control costs and the reduction in the species damages differ. The damages during the detection stage must be relatively larger than the costs of the control strategy ($p>c$) to justify employing any detection effort. The parameter value of the cost for the control strategy is much lower than the damages in the detection stage, thereby insuring that search is justified in these four cases. Many factors reduce the efficacy of search, thus the efficacy parameter, k, is assumed to be low for all cases to reflect the difficulty of successfully searching and detecting a species. While these parameters are assumed to be known in these examples, in reality, there is substantial uncertainty underlying them.

Figs. 1 and 2 plot the expected total costs and the present value of damages for the four types of species. The horizontal axis represents the search effort and the vertical axis represents the total costs (in thousands of dollars). The minimum of the expected total costs curve corresponds to the optimal search effort. The present value of damages, or the damages of the uncontrolled population, is a flat line since it does not depend on search effort.

Fig. 1 plots the expected total costs and present value of damages for cases 1 and 2. Case 1 illustrates a highly damaging species with a high growth rate. The curved solid line depicts the expected total costs (line 1) and the present value of damages is the flat solid line (line 2). With a highly damaging species, it is optimal to search at a relatively high level. Since the expected total costs curve is lower than the present value of damages for all levels of search effort, any level of resource allocation is better than taking no action when managing a high-damage species. The flatness of the expected total costs curve over a range of high levels of search effort suggests that for this type of invasive species, a wide range of intensive search strategies is close to the optimal. This is similar to findings in other papers focusing on investment in prevention activities; for high-damage species such as the gypsy moth or Emerald ash borer, even sub-optimal levels of resource allocation can be beneficial.

Case 2 represents a highly damaging species, similar to case 1, except that the species is more difficult to detect and has a lower growth rate. Even though the species is harder to detect than in case 1, the optimal strategy is to devote high levels of effort to searching (line 3). As in the previous case, it is better to take some action than to do nothing (line 4). The decreased curvature of the expected total costs curve suggests that it is sensitive to the efficacy and growth parameters. As a result, sub-optimal strategies are less costly than in the previous case.

Fig. 2 illustrates species exhibiting low growth rates and relatively lower damages than the previous cases. For case 3, the optimal search effort is low (line 1). However, it is still less costly to search than to forgo management (line 2). Case 4 represents a low-damage species with a smaller initial population size. In this situation, undertaking management (line 3) with sub-optimal effort levels is often more costly than not taking any action (line 4).

Table 1 – Parameter values and optimal search for four invasive species cases

Parameter values	Cases			
	Case 1	Case 2	Case 3	Case 4
Discount rate, r	0.1	0.1	0.1	0.1
Growth rate, a (month^{-1})	0.04	0.02	0.02	0.02
Initial population size, x_0	10	10	10	5
Detection parameter, k	0.005	0.003	0.005	0.005
Search costs, b (h^{-1})	\$50	\$50	\$50	\$50
Damages (detection stage), p	\$2,000	\$2,000	\$500	\$500
Costs (control stage), c	\$1,000	\$1,000	\$300	\$300
Optimal search, S^* (h)	61	48	23	9

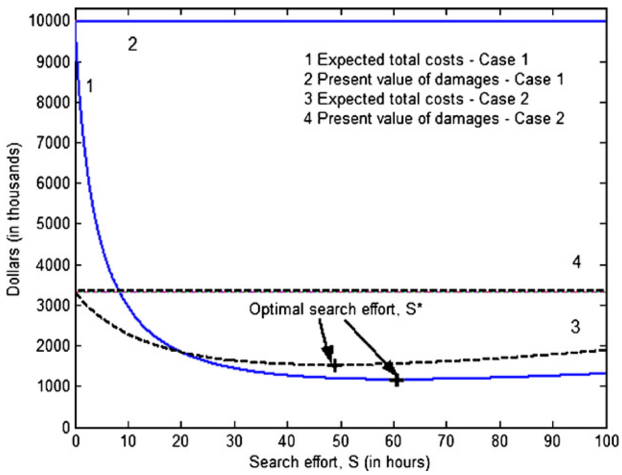

Fig. 1 – Cases 1 and 2: high damages. The curved solid line (1) represents the expected total costs of searching for case 1, a highly damaging species. The flat, solid line (2) represents the present value of damages no search is undertaken. The expected total costs for case 2 with search (the curved dashed line, 3) are similar although the optimal search effort is lower. The present value of damages (the flat dashed line, 4) is lower for case 2.

The optimal detection strategy is sensitive to several parameters, especially the detection and growth parameters and the initial population size. While all of these parameters are uncertain to some degree, research, past experiences and educated guesses can produce reliable estimates, justifying the assumption that these parameters are known. However, this is not the case for the initial population size which cannot be known prior to detecting the species. As shown in the next section, the uncertainty in the initial population size has a substantial effect on the optimal strategy.

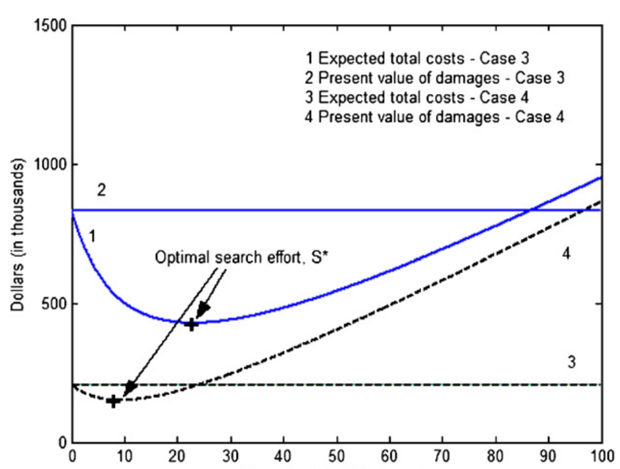

Fig. 2 – Cases 3 and 4: low damages. With relatively low damages and low growth rates, the optimal search effort for cases 3 and 4 is low. The optimal search effort for case 4 is close to taking no action owing to the low initial population size.

3.3. *Uncertainty in the initial population size*

Although the initial population size, x_0, is assumed to be known in the model, realistically, the manager will not know the population size prior to detection. Estimates can be derived once the species is found but not beforehand. This section relaxes the assumption of a known initial population size by incorporating an underlying probability distribution that governs the initial population size. Since species tend to remain at lower population sizes for long periods of time before growing significantly, the initial population size is modeled with an exponential distribution to reflect the prevalence of smaller initial populations:

$$f(x_0|\lambda) = \frac{1}{\lambda}e^{-x_0/\lambda} \qquad \text{where} \qquad E[f(x_0|\lambda)] = \lambda > 0 \tag{16}$$

λ is the scale parameter and $x_0 \geq 0$. A smaller λ represents the belief that the initial population size is smaller. The manager modifies the minimization problem in Eq. (4) to incorporate this stochasticity. Using the parameter values from case 1 (Table 1), the expected total costs for Fig. 3 are generated using Monte Carlo simulations for varying beliefs about the initial population size (λ = 1, 5, 10, and 15). The expected total costs and the optimal search intensity increase as the expected initial population size increases. In contrast, Fig. 4 graphs the expected total costs with deterministic initial population sizes that correspond to the expected populations sizes used in Fig. 3: x_0 = 1, 5, 10, and 15. The expected total costs are higher in the presence of uncertainty, as can be seen by comparing the expected costs in Fig. 3 with those in Fig. 4. The optimal search intensities are also higher under uncertainty, indicating that it is optimal to devote greater resources to searching when there is uncertainty about the initial population size.

3.4. *The effect of uncertainty on the detection parameter*

The efficacy of detection depends on several factors. Certain factors, such as technology, are known and remain constant

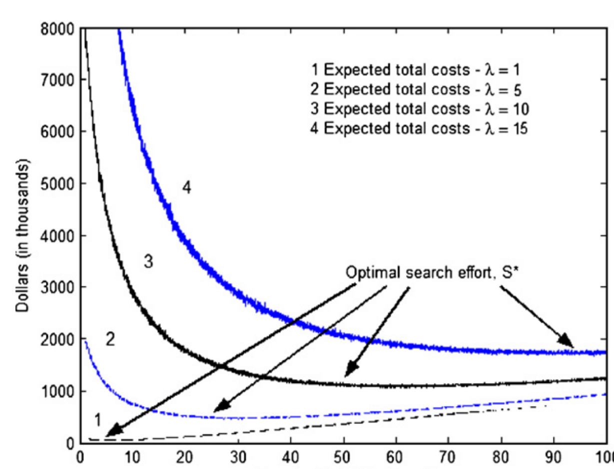

Fig. 3 – Expected total costs with uncertain initial population size. Using the parameter values for case 1, the expected total costs are simulated with initial population sizes drawn from an exponential probability distribution for varying value of the expected initial population size: λ = 1, 5, 10, and 15.

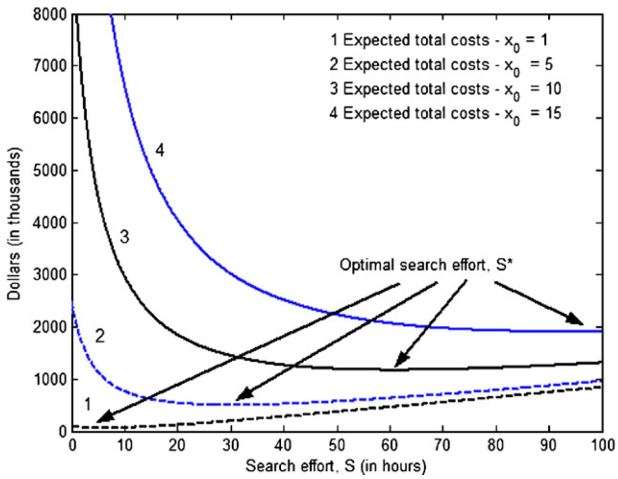

Fig. 4 – Expected total costs with known initial population size. Using parameter values for case 1, the expected total costs are plotted for different deterministic initial population sizes: x_0 = 1, 5, 10, and 15.

over time, while other factors, such as the visible damages, are stochastic and subject to change. Instead of treating the detection parameter, *k*, deterministically, the uncertainty underlying detectability can be captured via a probability distribution, $z(k|m)$. The parameter m ($m > 0$) acts as a proxy for the relationships that characterize the population, such as the initial population size and the natural growth rate of the species. The distribution function is continuous in *m* which is a strictly positive parameter. The probability distribution governing the time of detection, $q(\tau|S,k)$, is now a hierarchal distribution which subsumes the effects of search effort and uncertainty in detectability on the chances of successful species detection. As the population grows the chances of successfully detecting the species increase.

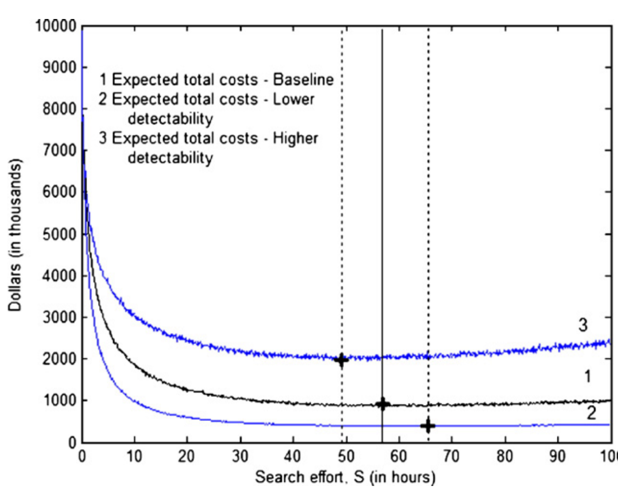

Fig. 5 – Expected total costs with stochastic detection parameter. Using parameter values for case 1, the expected total costs are plotted for varying levels of detectability. The optimal search efforts are fairly high regardless of the ease of detection.

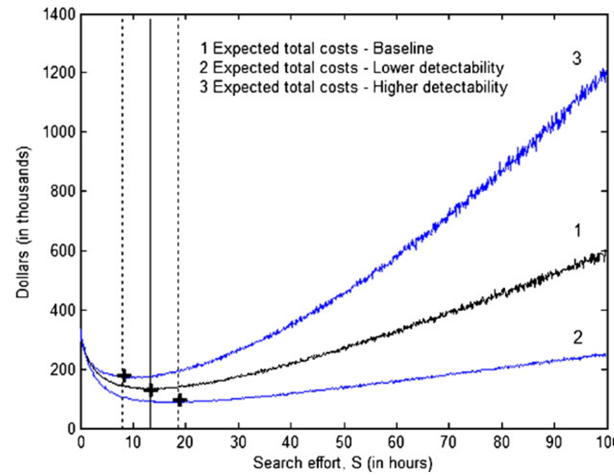

Fig. 6 – Expected total costs with stochastic detection parameter. Using parameter values for case 3, the expected total costs are plotted for varying levels of detectability. The optimal search efforts are fairly low due to the lower growth rates and low damages.

Figs. 5 and 6 plot the expected total costs using a Weibull distribution for $z(k|m)$. Each plot a baseline level of detectability and expected total costs for cases of lower and higher detectability. Fig. 5 illustrates varying levels of detectability for the parameter values for case 1. With higher detectability, the optimal search effort is lower since it is easier to find the species. The higher detectability represents a higher growth rate, a greater initial population size or larger visible damages; hence, the expected costs are also higher. Fig. 6 graphs the expected total costs for varying detectability levels for the parameter values of case 3. Since this species has a low growth rate and low damages, the optimal search effort is low regardless of the ease of detection.

4. Discussion

As the number of invasive species requiring management increases, agencies must identify efficient strategies for allocating resources to various species and management activities. Although conventional wisdom has emphasized prevention activities as the primary area for investment, the practical feasibility of increasing resources to prevention is questionable. Hence, the focus in invasive species management is shifting towards other activities, namely surveillance and monitoring activities that lead to early detection followed by swift implementation of control measures. Prior literature has focused predominantly on preventing introductions and post-detection control activities with little discussion of the role of detection activities in invasive species management. This paper serves as a first step in capturing the salient relationships underlying detection and control activities.

By using a simple model with stochastic and dynamic elements, we analyze the optimal constant detection strategy. The four simulations illustrate that for species with high damages, it is often optimal to devote significant resources to detection efforts even if the species is difficult to detect.

Current practices reflect this; they devote resources to detection even when the species has low detectability. On the other hand, several characteristics reduce the optimal level of search effort; these include the existence of a cost-efficient control strategy, low efficacy of search, and certain biological traits, such as low population densities or low growth rates.

Invasive species populations often remain at low levels for an extended period of time before their population starts to rise appreciably (at least in absolute terms). If the agency knows when a species might be reaching a critical period of growth, it might pay to search more at this stage when the probability of detection is likely to be higher. This fact would give rise to optimal search efforts that were not constant over time. However, in a more realistic and complex model with a stochastic date of introduction, a manager is unlikely to know when a species is introduced or to know the population growth stage of any particular invasive species at any time prior to detection. In this case, it is not unreasonable to identify policies for optimal constant search effort.

This model makes several simplifying assumptions that reflect aspects of invasive species management. These assumptions can be relaxed in future work to provide further insight into prominent biological and economic relationships:

1. policymakers often allocate fixed resources for certain actions over several time periods. The constant search effort in this model arises from such practices. However, if the search effort varies over time, new technology and knowledge can be incorporated to update beliefs and strategies. This can provide a richer discussion of policy-maker's decisions over time and the role of learning in informing policy decisions.
2. representing the uncertainty in the initial population size with an underlying probability distribution provides insight, but it still assumes some known distribution. Treating the initial population size as completely uncertain more closely represents the situation facing a government manager who does not have any belief about the population size prior to detection. Future work can expand upon this to evaluate the scenario where an agency must choose monitoring activities even though there is some probability that the species is not even present.
3. allocation decisions occur between numerous management activities. This basic model can be expanded to include other management activities. Several papers have discussed the prevention and post-detection stages, while this paper focuses on the detection and post-detection stages. Combining these three stages will capture the complete situation facing government agencies.
4. this model applies to a single species, but managers address several species simultaneously. Future work can expand this model to include the prioritization that occurs for managers allocating funds between various species.
5. although the spatial aspect is not explicitly discussed, implicitly, this paper assumes that the government agency is managing some parcel of land such as a forest, park, or farmland. The spatial aspect is a crucial, yet underemphasized aspect of invasive species management and future research should aim to incorporate the spatial dimensions.

As surveillance and monitoring activities occupy greater resources in invasive species management, analyzing the role of detection and its relationship with other management activities, through models such as this one, can help to better inform policy strategies.

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