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The Journal of Environmental Management is a journal for the publication of peer reviewed, original research for all aspects of management and the managed use of the environment, both natural and man-made. Critical review articles are also welcome; submission of these is strongly encouraged.

As governments and the general public become more keenly aware of the critical issues arising from man's use of his environment, this journal provides a forum for the discussion of environmental problems around the world and for the presentation of management results. It is aimed not only at the environmental manager, but at anyone concerned with the sustainable use of environmental resources.

Research Areas Include, but are not exclusive to:

• resource quality, quantity and sustainability • economics of environmental management • transport and fate of pollutants in the environment • spill prevention and management • remediation of contaminated sites • process modification for pollution prevention • improved energy efficiency • waste treatment and disposal

Papers submitted should address environmental management issues using a range of techniques e.g. case studies, observational and theoretical analyses, the application of science, engineering and technology to questions of environmental concern or mathematical and computer modeling techniques with the aim of informing both the researcher and practitioner.

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Economics of Invasive Species Management

Guest Editor: Ram Ranjan

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Editorial

Introduction: Special issue on the economics of invasive species management

This issue brings out some of the current thoughts on the economics of invasive species management. Through seven articles, it presents a collection of both empirical and theoretical works that explore various means to tackle the invasive species problems which threaten our agriculture and natural resources. Two of the papers in this issue deal with the important issue of managing invasive species at the port of entry; two papers do a bio-economic analysis for evaluating optimal strategies under risk and the timing of such strategies; one paper looks at the optimal harvesting of invasive species for obtaining value of information when the pest population is uncertain; one derives the distribution function for invasive species, arrival through existing data to analyse implications for detection efforts; and one looks at the valuation of ecological damages from invasive species.

Each invasive species presents its own set of unique challenges that is tied to its environment of origin and destination, biological characteristics, nature and extent of economic and ecological resources at risk, etc. Yet, the fundamental decision issues always involve spending costly resources to contain or eradicate them when there is limited information. When uncertainty is a key factor involved in decision-making, the timing, extent and robustness of decisions, generation of new information, and managing asymmetric information may have crucial implications for the success rate of invasive species management. These are precisely the issues that have been given special attention to in this special issue.

In the first paper, Ranjan et al. examine the optimal management of a renewable resource that is at risk from alien species invasion. The objective of this paper is to derive implications for optimal management of a resource when options exist for both preventing the arrival of an invasive species and mitigating the impact after arrival. Uncertainty about the timing and nature of an invasion can have important implications for the choice of management strategy, and a key feature of this analysis is an explicit treatment of that uncertainty.

The second paper by D'evelyn et al. asks whether control efforts could be used as an alternative to decipher the population stock of invasive species in the case when the effort-harvest function is stochastic but known. Early control efforts yield valuable information related to population size besides controlling the uncertain stock. They apply this idea to the study of brown tree snake control on the island of Saipan, located north of Guam.

Moffitt et al. design robust inspection protocols related to border inspections, a criterion that maximizes the range of uncertainty over which the damages from invasive species are restricted while meeting a budget constraint. Their approach offers another alternative to existing options for prevention. They do a numerical illustration of their idea for containerized agricultural cargo requiring inspection prior to entry into a country.

Areal et al. use the market for UK import of specific genera of cut flowers from Kenya between 1996 and 2004 as an example to study an invasion pathway along which species of non-indigenous plant pests can travel to reach new areas. Using the count data model they test for several models that fit species, arrival patterns. They highlight the importance of knowing the link between pest detection and the Genus of cut flower imported, as in some cases detection effort could be reduced without increasing the risks of species arrival and establishment.

Fernandez looks at two emissions vectors in the shipping industry—ballast water and biofouling, to address risk of damages under asymmetric information between the regulator and the shipper. She finds that incentive-based policies (subsidy with liability rule or tax with liability rule) are efficacious in avoiding marine invasive species pollution.

Grimsrud et al. examine the benefits of early detection and prevention of invasive weeds on grasslands. They find that the size of the incentive that is needed for weed management through private participation is dependent upon the level of infestation. Timing of incentives is crucial as higher incentive payments for lower levels of weed infestations reduce the total cumulative incentive payments over time.

The final paper of this issue deals with valuation of environmental damages by invasive species. The paper by Wilgen et al. estimates damages from 56 current and potential invasive species to the ecosystem of South Africa.

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The services considered are surface water runoff, groundwater recharge, livestock production and biodiversity. They find that the future damages from invasive species could be much higher than the current ones.

Guest Editor, JEM
Ram Ranjan
Economist, CSIRO, Perth, WA, Australia
E-mail address: ram.ranjan@csiro.au

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Optimal renewable resource management in the presence of endogenous risk of invasion

Ram Ranjan[a,*], Elizabeth Marshall[b], James Shortle[c,1]

[a]*CSIRO Land and Water, Private Bag 5, Wembley, WA 6913, Australia*
[b]*World Resource Institute, WA, USA*
[c]*Agricultural and Environmental Economics, Pennsylvania State University, 112A Armsby Building, University Park, PA, USA*

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Abstract

In this paper we examine the optimal management of a renewable resource that is at risk from alien species invasion. The objective of this paper is to derive implications for optimal management of a resource when options exist for both preventing the arrival of an invasive species and mitigating the impact of that arrival. Uncertainty about the timing and nature of an invasion can have important implications for the choice of management strategy, and a key feature of this analysis is an explicit treatment of that uncertainty.

Keywords: Endogenous risk; Invasive species; Renewable resource; Risk mitigation; Resilience; Poisson process

1. Introduction

Invasive species are emerging as a major environmental policy concern (Pimentel et al., 1999, 2000). The introduction of non-native plants, animals, viruses and other organisms into ecosystems has been recognized to be the largest source of ecosystem change and biodiversity loss in the world after habitat destruction (Glowka et al., 1994). There are numerous examples of the destructive impact of invasive species. The introduction of brown trout in New Zealand in 1862 has led to a complete elimination of the native Galaxiid fish today (Flecker and Townsed, 1994). Introduction of the Nile Perch to Lake Victoria caused the extinction of about 100 native fish species (McNeely, 2000). Introduction of the African Tilā̆pia into Lake Nicaragua caused the collapse of one of the world's unique freshwater ecosystems (McNeely, 2000). A well-known example of unintentional introduction is the case of zebra mussels (*Dreissena Polymorpha*) imported into the Great Lakes in ballast water; this non-native species has caused significant reduction in phytoplankton biomass and biofouling of man made structures (McIsaac, 1996). The value of fish catch alone in Lake Erie has gone down from $600 million in 1986 to $200 million in 1990 due to Zebra mussel invasion (McNeely, 2000). Invasive weeds have also been estimated to cost US farmers about $4 billion a year (Devine, 1998). Overall damages from invasives species are estimated to be much higher at about 138 billion dollars a year (Pimentel et al., 2005).

The risk of harmful invasions is increasing with the growth in international trade and tourism, and with climate change. Changes in climatic conditions can create favorable conditions for non-native species to establish themselves in new locations (Karevia et al., 1993; Stachowicz et al., 2002). Similarly, economic activities and biological invasions have been found to be positively correlated (Jenkins, 1996). With increasing international trade in agriculture, forestry, livestock, etc., alien species have been transmitted all over the globe. In Britain, for example, there have been more frequent incidents of the disease 'spring variaemia' since the relaxation of the import regime by the European Union in 1993 (The Economist, 2003). The cost of attempts to prevent such invasions in the

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*Corresponding author. Tel.: +61089336145.

E-mail addresses: ram.ranjan@csiro.au (R. Ranjan), jshortle@psu.edu (J. Shortle).

[1] Tel.: +814 865 7657; fax: +814 865 3746.

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United States has been very high. The General Accounting Office reports that the US government spends $600 million annually on combating invasive species (Hosansky, 2001). "Every year, the 2000 inspectors in the Agricultural Department's Animal and Plant Health Inspection Services (APHIS) face the Herculean task of checking some 50,000 ships, 1 million aircraft and tens of millions of travelers arriving from overseas with countless tons of cargo and packages" (Hosansky, 2001).

While a number of studies exist on the ecological aspects of species invasion, work related to the economic aspects of these invasions has only recently begun to emerge. Recent studies include those by Shogren (2000), Knowler and Barbier (2000), Eiswerth and Van Kooten (2002), Settle and Shogren (2002) and Eiswerth and Johnson (2002). The focus of this literature has been on the methods used to control the invaders without specific attention paid to the role of management of native species themselves for their survival and continuing economic productivity. Intuitively, the risk of losing a resource to invasion would, all other things being equal, reduce societal incentives to conserve the native species. This logic suggests that reduced conservation efforts and higher harvests would be the optimal response to the risk of invasion. However, if the resilience of the system is dependent on the stock of the native species itself, then the incentives for stock management may be reversed.

In cases where post-invasion survival and productivity of resources are stock dependent, the analysis of the invasive species management problem becomes much more complex. Notable in this regard is the study by Knowler and Barbier (2000) who analyze the economic losses from invasion in a dynamic predator–prey setting. They characterize the damages from invasion based upon the difference between the pre-invasion and post-invasion size of the native species stock. However, their model does not consider the possibilities of manipulating that difference through management of the pre-invasion stock or other prevention efforts.

In this paper we examine the optimal management of a renewable resource that is at risk from alien species invasion. The objective of this paper is to derive implications for optimal management of a resource when options exist for both preventing the arrival of an invasive species and mitigating the impact of that arrival. Uncertainty about the timing and nature of an invasion can have important implications for the choice of management strategy; a key feature of this analysis is an explicit treatment of that uncertainty. In our analysis, the uncertainty associated with an invasion is controllable through the preventive control measures and is thus endogenized.

The next section develops a model of a bio-economic system at risk of invasion. In the context of the model, we examine optimal rules for levels of native resource stock as well as prevention and mitigation effort. The analysis concludes with a numerical simulation illustrating the sensitivity of the optimal steady-state approach path to variation of important policy parameters.

2. The model

The literature on invasive species often divides the process of invasion into three phases: introduction of the species, establishment of the species and conversion into pests (Perrings, 2003). Invasive species can be managed through preventive, mitigative, and adaptive measures. Preventive measures address the first step in the process and include activities to eradicate or control potential invaders in their 'home locations' as well as measures to limit their movement into new territories. Examples of such efforts are requirements that ships eliminate ballast water before entering protected waters, and manual inspection of import goods such as timber that may carry harmful pests. We denote preventive efforts as ε_p.

Preventive activities will generally only help reduce the probability that an alien species will become introduced into a system. Mitigative measures address the second and third steps in the process, and are taken to limit damages after a species has been introduced into a new environment. Specifically, mitigative measures include steps taken to increase the resiliency of the resource in the wake of invasion by creating conditions that would limit the non-native species population, so that, although established, the extent of its impact on the native system is diminished. We denote mitigative efforts as ε_m.

Adaptive measures include more direct, post-invasion controls involving physical, chemical, or biological elimination of invasive species. They also include indirect methods of control such as change in consumption and production behavior in order to minimize the spread and damages from the established species. Although it would be possible to incorporate such strategies through the specification of the resource's post-invasion value function, we do not explicitly incorporate this management option into our model.

Our terminology differs slightly from that found in the previous literature. Perrings (2003) defines mitigation as "actions that reduce the *likelihood* of invasions by reducing the invasiveness of species or the invasibility of ecosystems", and adaptation as "actions that reduce *the impact of introduction, establishment or spread* without changing the likelihood that it will occur." Our use of the term "mitigation" is broader than Perrings' in that it refers to all pre-invasion actions that reduce the extent to which invading species can establish themselves. Mitigative efforts may still allow for invasions, but they endeavor to keep those invasions contained. Our use of the term "adaptation", on the other hand, is more narrow than Perrings' in that it refers solely to actions taken once the invading species has arrived and established itself in order to reduce the impact of that establishment and prevent spread. This allows us to separate efforts, and the costs of those efforts, temporally; mitigative efforts are purely pre-invasion, while adaptive efforts are purely post-invasion.

Our concept of resilience of a native system also requires further explanation. Ecological references to resilience usually conform to one of two possible definitions. Engineering resilience refers to "the rate at which a system returns to a single steady state or cyclic state following a perturbation" (Resilience Alliance, 2004). Ecological resilience, on the other hand, is measured by the amount of disruption or perturbation that is required to force a system to flip from one equilibrium state to another. See Holling (1973) and Gunderson et al. (2002) for more details on the concept of resilience. Our measurement of resilience, however, assumes that the nature of the post-disruption steady state may depend on the condition of the system prior to disruption. One could therefore manipulate the consequences of a system change by managing the system prior to disturbance. Stock dependent resiliency measures, for instance, may be appropriate when invading species need a critical biomass to thrive and displace the native species. A sufficiently high initial stock of native species may ensure that the alien species' population is constrained and never exceeds this critical level.

Our concept of resilience can therefore be viewed as some inverse measure of the distance between the pre-perturbation steady state and the post-perturbation steady state. According to this definition, the perturbation is assumed to be of a fixed magnitude, rather than variable as measured in ecological resilience. For a highly resilient system, the post-disturbance steady state may be exactly the same as the pre-disturbance steady state. For systems with low resilience, the fixed level of disturbance may force a shift to another steady state that is distant from the original steady state. Systems with intermediate levels of resilience may shift to steady states nearer to the original steady state.

In our model, the native system is composed of a renewable biological resource (e.g., a fishery) that is vulnerable to the introduction of an alien species into its habitat. Prior to invasion, the resource population grows according to

$$\dot{x}(t) = f(x) - h, \tag{1}$$

where x is the stock of renewable resource at any instant of time, $f(x)$ is a concave growth function and h is the harvest rate.

It is assumed that prior to invasion, instantaneous benefits received from the resource are represented by

$$b(h) - c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) - c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}), \tag{2}$$

where the net benefit from the harvest is denoted by $b(h)$, the costs of preventive control measures are denoted $c_{\mathrm{p}}(\varepsilon_{\mathrm{p}})$, and the costs of mitigative control measures are denoted $c_{\mathrm{m}}(\varepsilon_{\mathrm{m}})$. Note that in this notation we have suppressed the time argument in favor of a simpler presentation.

The methodology used for modeling the risk of invasion in this system is based on the work of Clarke and Reed (1994) and Gjerde et al. (1999). The risk of invasion is modeled using a survival function to represent the ecosystem's likelihood of surviving in the pre-invasion state into each time period, t. Let T be the moment of ecosystem invasion. The cumulative probability distribution associated with invasion is denoted $F(t)$, where $F(t) = \Pr(T < t)$. The survivor function captures the probability that an invasion has not yet occurred in time t, and represents the upper tail of the cumulative probability distribution:

$$S(t) = Pr(T \geqslant t) = 1 - F(t). \tag{3}$$

In each time period it is assumed that, conditional upon arriving in time t without yet having been invaded, the system faces a certain probability of transition into the post-invasion state, denoted $p(t)$. This conditional probability, $p(t)$, is also referred to as the hazard rate. Using a Poisson distribution to represent the probability of invasion, we model the probability of invasion in any interval $\mathrm{d}t$ as $p(t)\,\mathrm{d}t$, and

$$F(t) = 1 - \mathrm{e}^{-\lambda(t)}, \tag{4}$$

where

$$\lambda(t) = \int_0^t p(\varepsilon_{\mathrm{p}}(s))\,\mathrm{d}s \tag{5}$$

and

$$\dot{\lambda}(t) = p(\varepsilon_{\mathrm{p}}(s)), \tag{6}$$

where $p(\varepsilon_{\mathrm{p}}(s))$ is the hazard rate affected by preventive efforts. The probability of surviving until any time period t without being invaded is, therefore, $\mathrm{e}^{-\lambda(t)}$. In this formulation, λ is used as a surrogate state variable that captures the endogeneity of the risk of invasion. This approach is based upon Clarke and Reed (1994). The unconditional probability of invasion in an exact period t is the probability of both being invaded in period t and not having been invaded prior to that period:

$$p(\varepsilon_{\mathrm{p}}(t))\mathrm{e}^{-\lambda(t)}. \tag{7}$$

Once the system suffers an invasion, it becomes less productive. The value of the ecosystem in the post-invasion state is given by the function $V(*)$, representing the present value of total discounted future returns in the post-invasion state, contingent on the management of the resource. We assume that both pre- and post-invasion the resource is optimally managed. We will discuss the value function in more detail below.

Prior to invasion, an economically optimal plan maximizes returns to the renewable resource over an infinite time horizon by optimally choosing pre-invasion levels of harvest, preventive control efforts, and mitigative control efforts. Specifically, the objective function is[2]

$$J = E\left[\int_o^T (b(h) - c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) - c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}))\mathrm{e}^{-rt}\,\mathrm{d}t + V(*)\mathrm{e}^{-rT}\right]. \tag{8}$$

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[2] We omit the time argument in the variables to simplify the presentation.

As mentioned above, mitigative efforts can be used to buffer the impact of invasive species. The translation of mitigative effort into an increase in ecosystem resilience can take many forms depending on the nature of the resource and the expected nature of the invasive species. It is assumed that some measure of resilience exists, denoted a, that accumulates over time as a result of mitigative efforts. The evolution of the resilience parameter is given by

$$\dot{a} = q(\varepsilon_{\mathrm{m}}) - d(a), \tag{9}$$

where $q(\varepsilon_{\mathrm{m}})$ represents the effect of mitigative efforts on resiliency and $d(a)$ is a natural rate of decay of system resilience and $\dot{a}$ is the time derivate of resilience. This decay rate is incorporated in order to accommodate the possibility that exogenous changes to the system could facilitate establishment of an invading species through mechanisms other than a reduction in native stock. It also makes our analysis of the steady state easier. However, in specific cases where no such external decay exists, a steady-state analysis can be done nevertheless by a redefinition of variables. Thus, results from this study are fairly generalizable. Further, we assume $q'_{\varepsilon_{\mathrm{m}}} > 0$, $d'_a > 0$. One can therefore use mitigative efforts to invest in ecosystem resilience, but it is not possible to maintain a given resilience level without continuing maintenance efforts.

One example of a mitigative effort that can be expected to increase the resilience of the bio-economic system is maintenance of a healthy pre-invasion stock level. This tool is somewhat unique, however, in that its costs are not reflected in an increase in $c_{\mathrm{m}}(\varepsilon_{\mathrm{m}})$, but rather in a decrease in returns from harvesting. Accordingly, we incorporate this tool into the general model independently of other mitigation efforts. In doing so, we must create a distinction between the component of resilience that is generated by overall ecosystem health (as measured by a), and the component of resilience generated by stock levels (as measured by x). Resilience of the entire bio-economic system is a function of both a and x; once invasion has taken place, both variables together determine the post-invasion carrying capacity of the resource. The value function in the post-invasion state can therefore be characterized by $V(a, x)$, where $V_a > 0$, $V_x > 0$, $V_{aa} < 0$, $V_{ax} < 0$, $V_{xx} < 0$.

Entry of the invasive species could impact productivity by affecting either the carrying capacity of the native environment or the intrinsic growth rate of the native population through competition or predation. In this system we assume that invasion affects the system's carrying capacity for the native species. This assumption would be appropriate in cases where the invading species (not necessarily a prey) compete for space with the native species in order to establish their niche. The emptier the environment is left from a lower host population, the higher would be the invading species population. When the native and the invading species compete for scarce resources, a higher invading species population would mean a lower carrying capacity for the host species. In such cases, the stock of the native species at the time of invasion could play a crucial role in determining the post-invasion value function through its eventual carrying capacity. Although the costs of mitigative efforts such as stock maintenance may be borne throughout the pre-invasion period, the benefits are felt only post-invasion and therefore enter the manager's decision problem through their impacts on the post-invasion value function, $V(a, x)$.

With this specification, Eq. (8) becomes

$$J = \int_0^{\infty} \mathrm{e}^{-rt-\lambda(t)}(b(h) - c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) - c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) + p(\varepsilon_{\mathrm{p}})V(a, x))\,\mathrm{d}t. \tag{10}$$

Note that the probability of invasion enters this expression in two ways. The first is through the probability of surviving to time period t (and realizing returns in that period), and the second through the probability of collapsing in exactly time period t (thereby realizing the post-invasion value function in that period).

The management problem is to maximize (10) with respect to h, ε_{p} and ε_{m} subject to (1), (6) and (9):

The current value Hamiltonian is given by

$$\begin{aligned}\mathrm{CVH} = {} & \{b(h) - c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) - c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) + p(\varepsilon_{\mathrm{p}})V(x, a)\}\mathrm{e}^{-\lambda(t)} \\ & + \mu_1(f(x) - h) + \mu_2 p(\varepsilon_{\mathrm{p}}) + \mu_3(q(\varepsilon_{\mathrm{m}}) - d(a)).\end{aligned} \tag{11}$$

The co-state variables in this expression are expected values. To simplify the analysis, we replace them as follows:

$\rho_1 = \mathrm{e}^{\lambda}\mu_1$, $\rho_2 = \mathrm{e}^{\lambda}\mu_2$, and $\rho_3 = \mathrm{e}^{\lambda}\mu_3$.

These new variables represent conditional shadow values for the state variables (Clarke and Reed, 1994). They are conditional at time t on no invasions having occurred prior to that point in time. Following Pontryagin's Maximum Principle, the first-order conditions for optimal harvests, prevention and mitigation investment are[3]:

$$\rho_1 = b'(h), \tag{12}$$

$$[\rho_2 + V(x, a)]p'(\varepsilon_{\mathrm{p}}) = c'_{\mathrm{p}}(\varepsilon_{\mathrm{p}}), \tag{13}$$

$$\rho_3 q'(\varepsilon_{\mathrm{m}}) = c'_{\mathrm{m}}(\varepsilon_{\mathrm{m}}), \tag{14}$$

$$\dot{\rho}_1 = -p(\varepsilon_{\mathrm{p}})V'_x(x, a) + b'(h)(-f'(x) + r + p(\varepsilon_{\mathrm{p}})), \tag{15}$$

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[3] We also need to ensure that the necessary conditions for maximization of the Hamiltonian are the sufficient ones. If solution of the first order conditions yields adjoint variables of the expected sign ($\mu_1^*(t) \geqslant 0$, $\mu_2^*(t) \leqslant 0$, $\mu_3^*(t) \geqslant 0$), then the following additional conditions ensure that the necessary conditions are also sufficient conditions: $b''(h) \leqslant 0$, $p''(\varepsilon_{\mathrm{p}}) \leqslant 0$, $c''_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) \geqslant 0$, $c''_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) \geqslant 0$, $V''_{aa}(x, a) \leqslant 0$. Where not noted above, these conditions are assumed. These conditions were derived using the MathEcon program in Mathematica and can be made available upon request.

$$\dot{\rho}_2 = b(h) - c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) - c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) + \frac{c'_{\mathrm{p}}(\varepsilon_{\mathrm{p}})}{p'(\varepsilon_{\mathrm{p}})}(r + p(\varepsilon_{\mathrm{p}})) - rV(x, a), \tag{16}$$

$$\dot{\rho}_3 = -p(\varepsilon_{\mathrm{p}})V_a(x, a) + (p(\varepsilon_{\mathrm{p}}) + r + d'(a))\frac{c'_{\mathrm{m}}(\varepsilon_{\mathrm{m}})}{q'(\varepsilon_{\mathrm{m}})}. \tag{17}$$

Eq. (12) requires that the marginal benefits from harvest be equated to the conditional shadow price of the resource stock. Eqs. (13) and (14) require the marginal benefits of prevention and mitigation activities, on the LHS of (13) and (14) respectively, to equal the respective marginal costs on the RHS. The marginal benefit of prevention is the product of the marginal change in the instantaneous hazard rate, $p'(\varepsilon_{\mathrm{p}})$, which is negative, and the sum of the conditional shadow cost of the hazard rate, ρ_2, and the post-invasion value function, $V(x, a)$. The value function appears as a deduction from the value of preventive control measures in the expression because prevention postpones post-invasion rewards. Clearly, for prevention measures to be worthwhile, the expected gains from expenditures to reduce the instantaneous hazard rate (i.e., ρ_2 at the margin) must exceed the post-invasion value. Similarly, the marginal benefit of investments in resilience is the product of the conditional shadow value of increased resilience and marginal contribution of the investments to resilience. Eqs. (15)–(17) are arbitrage conditions for the state variables. For efficiency of exposition, we examine their interpretation in the pre-invasion steady state.

The pre-invasion steady state is defined as a scenario in which

$\dot{h} = 0,\ \dot{\varepsilon}_{\mathrm{m}} = 0,\ \dot{\varepsilon}_{\mathrm{p}} = 0,\ \dot{x} = 0,\ \dot{a} = 0,\ \dot{\rho}_1 = 0,\ \dot{\rho}_2 = 0$ and $\dot{\rho}_3 = 0$.

The harvest and preventive effort levels at the steady state are clearly determined by the optimization constraints (12) and (13). The remaining conditions imply that in the steady state:

$$b'(h)(r + p(\varepsilon_{\mathrm{p}}) - f''(x)) = p(\varepsilon_{\mathrm{p}})V'_x(x, a), \tag{18}$$

$$c'_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) = \frac{\{-b(h) + c_{\mathrm{p}}(\varepsilon_{\mathrm{p}}) + c_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) + rV(x, a)\}p'(\varepsilon_{\mathrm{p}})}{(r + p(\varepsilon_{\mathrm{p}}))}, \tag{19}$$

and

$$c'_{\mathrm{m}}(\varepsilon_{\mathrm{m}}) = \frac{p(\varepsilon_{\mathrm{p}})V'_a(x, a)q'(\varepsilon_{\mathrm{m}})}{(p(\varepsilon_{\mathrm{p}}) + r + d'(a))}. \tag{20}$$

Using Eq. (18) we can express the steady-state resource stock arbitrage condition as

$$r + p(\varepsilon_{\mathrm{p}}) = f''(x) + \frac{p(\varepsilon_{\mathrm{p}})(V_x)}{b'(h)}. \tag{21}$$

Note that the instantaneous hazard rate $p(\varepsilon_{\mathrm{p}})$ enters on both sides of the equation. On the left-hand side its effect is to raise the effective rate of discount, thus making future returns less valuable. On the right-hand side it moderates the importance of the ratio of the marginal value from stock in the post entry scenario relative to the current marginal value of harvest in determining stock size. In the absence of any risk of an invasion, the pre-invasion steady-state stock would solve $f'(x) = r$, as has been well known. However, in the presence of such uncertainty about an invasion, the steady-state condition requires that the change in the growth of stock plus the rise in expected value in the post-invasion state relative to pre invasion marginal benefits from harvest must equal the effective rate of discount as defined by $(r+p(\varepsilon_{\mathrm{p}}))$.

For additional insight, it is possible to derive an alternative expression for the steady-state arbitrage condition:

$$f'(x) + p(\varepsilon_{\mathrm{p}})\left(\frac{V'_x(x, a) - b'(h)}{b'(h)}\right) = r. \tag{22}$$

The second term on the LHS is the expected growth rate of the difference between the marginal value of the post-invasion state and the marginal benefits of the pre-invasion state. It's sign depends on the relative magnitude of $V_x'(x, a)$ and $b'(h)$. If $V''_x(x, a) - b'(h) > 0$, and assuming that stock growth follows a concave path, then the steady-state resource stock would be higher than without the risk of invasion. This is consistent with intuition; if the marginal increase in the post-invasion value function is greater than the marginal benefits of current harvests, then a positive instantaneous hazard rate generates an incentive to maintain a higher stock of the renewable resource. Under these circumstances, it is beneficial to forego some harvest benefits today in order to reap higher benefits in the event of invasion.

On the other hand, if marginal benefits from current harvest are relatively high as compared to the marginal value from incremental stock in the post-invasion state, then the possibility of collapse and loss of current harvest benefits may generate the reverse incentive. It may in that case be beneficial to extract more, so that the steady-state stock level in the presence of uncertainty, denoted $x^*_{\text{pre-invasion}}$, will be lower than $x^*_{\text{no-risk}}$. In both cases, the extent to which $x^*_{\text{pre-invasion}}$ differs from $x^*_{\text{no-risk}}$ depends on the magnitude of the hazard rate; as the hazard rate increases, so too does the magnitude of the difference between the two steady states. If the risk of collapse is very small, there is little incentive for the value of marginal post-invasion stock benefits relative to the marginal pre-invasion harvest benefits to affect the steady-state stock limit, and in the limit the stock size tends toward that size at which $f'(x) = r$.

Comparative static analysis can also be used to explore how steady-state levels of preventive and mitigative effort are expected to vary with the discount rate, r. Using the implicit function theorem Eq. (18) gives us

$$\frac{\mathrm{d}\varepsilon_{\mathrm{p}}}{\mathrm{d}r} = -\frac{b'(h)}{p'(\varepsilon_{\mathrm{p}})(b'(h) - V'_x(x, a))}. \tag{23}$$

Clearly, a higher discount rate increases the relative value of present returns, but the effect this has on preventive efforts is ambiguous. Again, the nature of the effect depends on the relative magnitudes of $b'(h)$ and $V'_x(x, a)$. When the marginal post-invasion value of stock is low relative to the marginal pre-invasion return to harvest, so that $b'(h)-V'_x>0$, optimization requires that the hazard rate be reduced by taking further preventive controls. As discussed earlier, this scenario is also characterized by a steady-state stock level that is less than the no-risk stock $x^*_{\text{no-risk}}$.

Alternatively, when the marginal post-invasion values of stock are relatively high, an increase in the discount rate results in a decrease in preventive efforts. In this case, it is more worthwhile to mitigate the possible impacts of invasion through costs associated with stock management and foregone harvest rather than through preventive efforts.

Further analysis of the role of preventive efforts can be derived from Eq. (19):

$$c'_{\text{p}}(\varepsilon_{\text{p}}) = \frac{-\{b(h) - c_{\text{p}}(\varepsilon_{\text{p}}) - c_{\text{m}}(\varepsilon_{\text{m}}) - rV(x,a)\}p'(\varepsilon_{\text{p}})}{(r + p(\varepsilon_{\text{p}}))}. \tag{24}$$

The right-hand side is the discounted value of the change in current period expected returns due to a marginal increase in preventive efforts. The left-hand side is the marginal cost of such an effort. Note that the hazard rate enters the right-hand side both in the numerator and in the denominator. In the numerator it enters through the marginal effect on the hazard rate generated by preventive efforts, whereas in the denominator it appears as the actual probability of transition. Clarke and Reed (1994) refer to these as the policy dependent and policy independent effects, respectively. If the preventive efforts are not very effective in reducing the hazard rate, the numerator would change by a very small amount, thus raising the marginal costs of such efforts substantially. On the other hand if the hazard rate that faces an ecosystem (or policy-independent value) is very high to begin with, post-invasion values would be severely discounted anyway, thus prompting little or no preventive efforts.

Using the implicit function theorem, the impact of the discount rate on the optimal mitigative efforts is derived as follows:

$$\frac{\mathrm{d}\varepsilon_{\text{m}}}{\mathrm{d}r} = \frac{-c'(\varepsilon_{\text{m}})^2}{\{c''(\varepsilon_{\text{m}})q'(\varepsilon_{\text{m}}) - q''(\varepsilon_{\text{m}})c'(\varepsilon_{\text{m}})\}p(\varepsilon_{\text{p}})V'_a}. \tag{25}$$

According to this formula, mitigative efforts increase with r if:

$$\frac{c''(\varepsilon_{\text{m}})}{c'(\varepsilon_{\text{m}})} < \frac{q''(\varepsilon_{\text{m}})}{q'(\varepsilon_{\text{m}})}. \tag{26}$$

A higher discount rate will therefore result in greater mitigative efforts only if the marginal effect of mitigative efforts on system resilience is increasing faster than the marginal cost of those efforts. If marginal costs of mitigative efforts were increasing faster than their marginal benefits, an increase in the discount rate would lead to a decline in mitigative efforts.

3. A numerical simulation

We perform a numerical simulation to provide additional insight about the optimal time paths of preventive and mitigative efforts, and the tradeoffs that are generated with the optimal stock and harvest levels. Unlike the qualitative analysis in the preceding section, numerical solution of the post-invasion system requires explicit modeling of the post-invasion state to obtain the post-invasion value function. Sufficient structure in the pre- and post-invasion states is imposed to allow a closed form solution of the value function and numerical computation of the pre-invasion optimal management. Specifically, in the pre-invasion state, we assume:

$$b(h) = bh \Rightarrow \text{Constant marginal returns from harvest}, \tag{27}$$

$$c_{\text{p}}(\varepsilon_{\text{p}}) = c_{\text{p}}\varepsilon_{\text{p}} \Rightarrow \text{Constant marginal cost of } \times\text{preventive control}, \tag{28}$$

$$c_{\text{m}}(\varepsilon_{\text{m}}) = c_{\text{m}}\varepsilon_{\text{m}} \Rightarrow \text{Constant marginal cost of } \times\text{mitigative control}, \tag{29}$$

$$p(\varepsilon_{\text{p}}) = p_0 \mathrm{e}^{-\varepsilon_{\text{p}}} \Rightarrow \text{Variable marginal product of } \times\text{preventive control}, \tag{30}$$

$$f(x) = \rho x(1 - x/K), \text{ where } \rho \text{ is the } \times\text{intrinsic growth rate}, \tag{31}$$

$$K_1 = \alpha K_0, \tag{32}$$

where K_0 is the pre-invasion carrying capacity of the system and K_1 is the post-invasion carrying capacity of the system. Invasion adversely affects the carrying capacity of the native environment, as mediated by the parameter $\alpha = g(a, x)$. The relationship between α and its driving variables is defined by

$$\alpha = 1 - \mathrm{e}^{-\eta x(t)^{\tau} a(t)^{1-\tau}}, \tag{33}$$

which restricts α to lie between 0 and 1. The variable τ defines the relative importance of $x(t)$ and $a(t)$ in determining ecosystem resilience. η merely serves as a conversion variable that translates variation in $x(t)$ and $a(t)$ into a scale that impacts variation of α. The variable a is assumed to evolve according to the equation $\dot{a} = a_0 + \varepsilon_{\text{m}}t$. Note that for simplicity the exogenous rate of decay is assumed to be zero and the level of mitigative efforts fixed constant all throughout. This constant level is however, optimally derived.[4]

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[4] It may not be possible to solve for an endogenous value function while allowing for a varying mitigative effort over time.

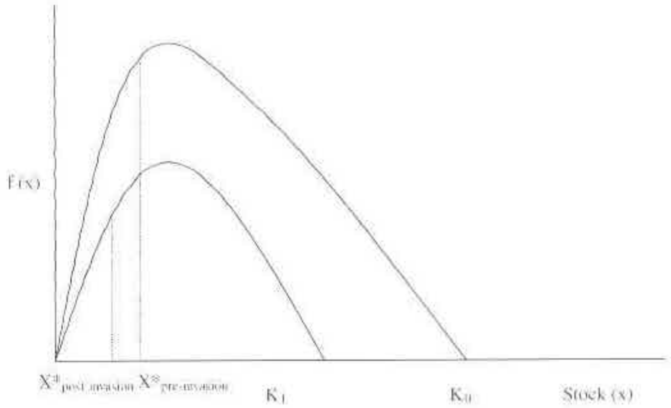

Fig. 1. Stock growth.

The biological growth equation for stock is given by Eq. (31) and in the post-invasion state incorporates the reduced carrying capacity, K_1. Note that K_1 is a function of both x and a, which are themselves time dependent. Fig. 1 depicts the reduced carrying capacity due to invasion and possible implications for the steady-state stock levels prior to and after invasion.

The post-invasion management problem is to maximize:

$$\int_T^\infty (bh)\mathrm{e}^{-rt}, \text{ s.t.,} \tag{34}$$

$$\dot{x}(t) = f(x) - h. \tag{35}$$

Since the Hamiltonian of this problem is linear in the control, the solution is obtained by using a most rapid approach path analysis. The steady-state stock in the post-invasion state is

$$x^*_{\text{post-invasion}} = \frac{K_1(x,a)}{2\rho}(\rho - r). \tag{36}$$

Now, if the invasion occurs at some level of stock x_T, then the optimal control involves:

$$\text{Set } h = \left\{ 0 \quad \text{if } x_T \leqslant x^*_{\text{post invasion}} \text{ and} \right.$$
$$\left. \text{MAX if } x_T > x^*_{\text{post invasion}} \right\}. \tag{37}$$

In the above, MAX is the maximum harvest possible at any instant. For the sake of simplicity we assume that this exceeds $x_T - x^*_{\text{post-invasion}}$ for any level of x_T. The value function in the post-invasion state is given by

$$V_{x_T \leqslant x^*_{\text{post invasion}}} = \int_{T+\tilde{T}}^\infty bh^*\mathrm{e}^{-rt}\,\mathrm{d}t = \frac{bh^*}{r}\mathrm{e}^{-r(T+\tilde{T})}, \tag{38}$$

if $x_T \leqslant x^*_{\text{post-invasion}}$. Here h^* is the harvest rate required to keep the stock at the post-invasion steady-state stock level and is given by

$$\rho x^*_{\text{post-invasion}}\left(1 - \frac{x^*_{\text{post-invasion}}}{K_1(x,a)}\right) = h^*, \tag{39}$$

where $\tilde{T}$ is the time it takes for the stock to grow from its level at the time of invasion, x_T, to $x^*_{\text{post-invasion}}$ and is given by

$$\tilde{T} = \frac{-1}{\rho}\operatorname{Log}\left\{\frac{x_T(K_1(x,a) - x^*_{\text{post-invasion}})}{x^*_{\text{post-invasion}}(K_1(x,a) - x_T)}\right\}. \tag{40}$$

If $x_T > x^*_{\text{post-invasion}}$, it is possible to instantly harvest the surplus stock and begin to operate at the post-invasion optimal harvest level. The value function is given by

$$\begin{aligned} V_{x_T \geqslant x^*_{\text{post invasion}}} &= (x_T - x^*)b\mathrm{e}^{-rT} + \int_T^\infty bh^*\mathrm{e}^{-rt}\,\mathrm{d}t \\ &= (x_T - x^*)b\mathrm{e}^{-rT} + \frac{bh^*}{r}\mathrm{e}^{-rT}. \end{aligned} \tag{41}$$

It is not possible to determine *ex ante* whether the system will be invaded before the stock level reaches the point at which $x(t) = x^*_{\text{post-invasion}}$. Accordingly, while maximizing the net benefits in the 'pre-invasion' state, the appropriate post-invasion value function is the expectation over the two state-contingent value functions described above. The optimal control problem for the above example with the hazard structure described earlier can then be stated as

$$\begin{aligned} U_0 = \text{Max} &\int_0^\infty (b(h) - c(\varepsilon_p) - c(\varepsilon_m))\mathrm{e}^{-rt-\lambda(t)}\,\mathrm{d}t \\ &+ \int_0^{\tilde{T}} p(\varepsilon_p)\mathrm{e}^{-\lambda(t)}\frac{bh^*}{r}\mathrm{e}^{-r(t+\tilde{T})} \\ &+ \int_{\tilde{T}}^\infty p(\varepsilon_p)\mathrm{e}^{-\lambda(t)-rt}\left[\{x(t) - x^*_{\text{post-invasion}}\}b + \frac{bh^*}{r}\right]\mathrm{d}t. \end{aligned} \tag{42}$$

This maximization is subject to Eqs. (1), (6) and (9). The first term in Eq. (42) represents the expected value of pre-invasion returns, and is represented by the weighted sum of returns in each period multiplied by the probability of surviving into that period without invasion. The time period in which the stock of renewable resource equals its own post-invasion steady state is denoted $\tilde{T}$.

The latter two terms in Eq. (42) represent the expected post-invasion value function. To calculate the expected post-invasion value function, the optimization must be split into two terms, one representing the period where $x(t)$ is less than its associated post-invasion steady-state stock level, $x^*_{\text{post-invasion}}$, and the other representing the period when $x(t)$ exceeds its post-invasion steady-state stock level. Due to logistic growth, the stock of resource, $x(t)$, at any instant during the transition to $x^*_{\text{pre-invasion}}$ can be deduced as a function of its initial level, x_0:

$$x(t) = \frac{K_0}{1 + \mathrm{e}^{-\rho t}[(K_0 - x_0)/x_0]} \tag{43}$$

The post-invasion steady-state stock level, however, is also changing over time. The optimal post-invasion stock level is endogenous because it depends upon the level of ecosystem resilience, and therefore on the level of stock (together with mitigative effort), at any given point in time. As illustrated in Fig. 2, this optimal post-invasion stock level rises with $x(t)$ at a declining rate due to the functional form of the resilience variable defined earlier. The time period in which the two curves intersect represents that period in which the stock of renewable resource equals its own post-invasion steady state. This time period is denoted $\hat{T}$ and the length of time it takes to move from x_0 to the stock level where $x_0 = x^*_{\text{post-invasion}}$ is calculated by

$$\hat{T} = \frac{-1}{\rho}\,\mathrm{Log}\left\{\frac{x_0(K_0 - x^*_{\text{post-invasion}})}{x^*_{\text{post-invasion}}(K_0 - x_0)}\right\}. \tag{44}$$

It is not possible to analytically solve for the value function without assuming some form for the survival function. Eq. (30) above describes the nature of the hazard function, where p_0 is the policy independent hazard rate. However, the time path of the preventive control still needs to be derived in order to solve the two components of the value function. In the simulation, mitigation efforts are assumed to be at an optimally chosen but constant level throughout the pre-invasion period in order to simplify the solution procedure.

Numerical simulations are performed using GAMS to study the effects of parameters on the optimal time paths for the stock and control variables. We consider the case where the initial stock of resources, x_0, is below both $x^*_{\text{post-invasion}}$ and $x^*_{\text{pre-invasion}}$. This could, for instance, reflect a resource that is moving out of common-property management, and has therefore tended to be overexploited. Cases involving an initial stock of resources between $x^*_{\text{post-invasion}}$ and $x^*_{\text{pre-invasion}}$ could be handled in a fairly straightforward fashion but are unlikely to provide additional insight. The above model was solved for the hypothetical set of parameters described in Table 1. A time horizon of 200 years is used to approximate an infinite horizon problem.

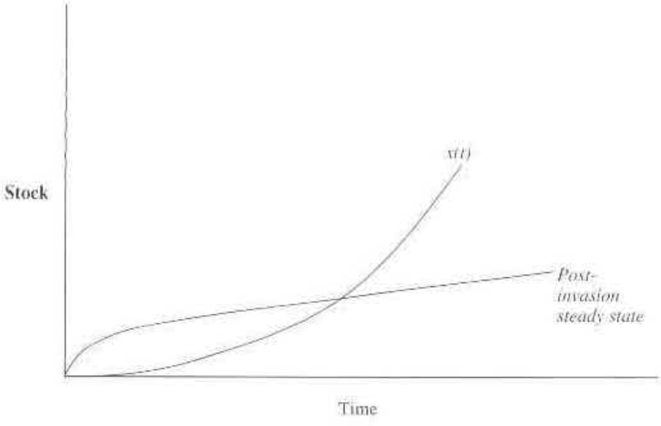

Fig. 2. The intersection of stock of renewable resource with the post-invasion steady-state stock.

The following figures illustrate the results of the numerical simulation. These figures describe the planned pre-invasion paths for state and control variables given a probability of invasion but with no certainty of when that invasion might be. Should invasion occur at any point along the paths illustrated, the system would proceed toward the post-invasion optimum associated with that transition point. Post-invasion behavior is not illustrated in the figures below.

The time paths of the evolution of resilience for the numerical models are described in Fig. 3. Note that every system's optimal path prior to invasion involves convergence toward a resilience of 1; this result is inevitable for a positive optimal mitigation level, as there is no natural decay in the ecosystem resilience variable. A resilience level of 1 implies that there is no longer any threat from invasion; the system is healthy enough to rebuff all intruders and no difference exists between the pre-invasion and post-invasion states. What differs between the cases, however, is the rate at which resilience builds, the relative importance of stock versus mitigative efforts in the process of building and maintaining resilience, and the role of preventive measures during the transition.

Figs. 4 and 5 illustrate the relevant numerical variable results for this analysis. The optimal pre-invasion resource stock level for various parameter sets is shown in Fig. 4. The rate of increase in stock is always determined purely by biological growth rates, but the scenarios differ in how large stock is allowed to grow before harvest is initiated.

Table 1
Parameters and cases

Parameters Cases	r	ρ	$C(\varepsilon_{\text{m}})$	$C(\varepsilon_{\text{p}})$	h	p_0	k_1	T	η	a_0	α_1	x_0
Base case	.005	.1	.05	.05	1	.01	100	200	.05	5	.5	10
High harvest benefits					5							
High policy independent hazard rate						.05						
High preventive costs				1								
Low mitigative costs			.005									
High mitigative costs			.5									
High discount rate	.01											
High growth rate		.25										

Note: see the numerical section for details on the parameters. Parameters that were not tweaked for sensitivity analysis are a_0, α_1, x_0, k_1, and η. These parameters were not used for sensitivity analysis as the resulting dynamics form their variation is fairly obvious and does not add much to our purposes.

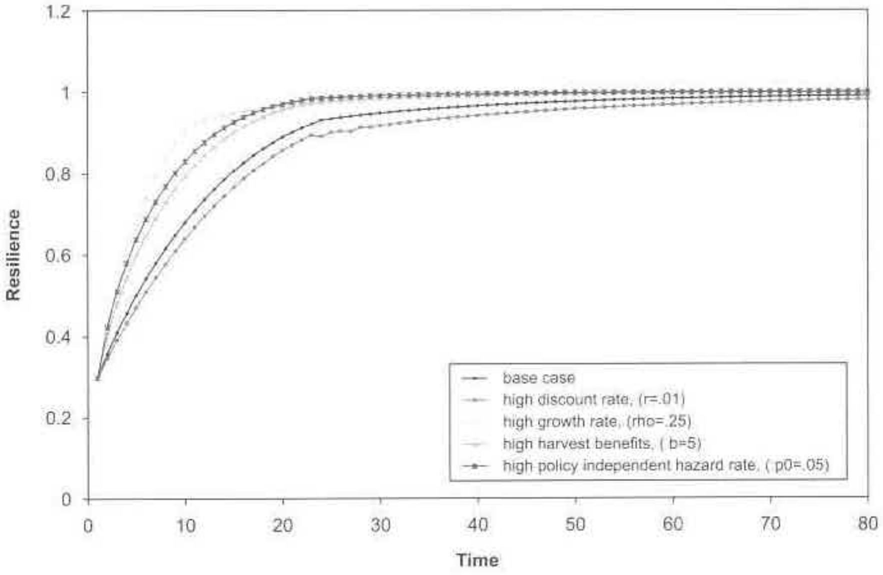

Fig. 3. Evolution of ecosystem resilience.

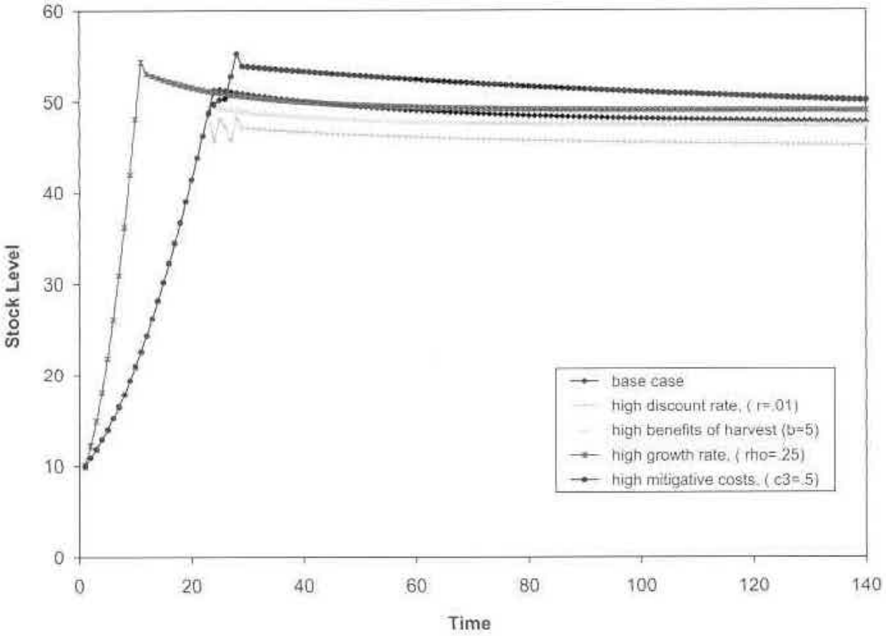

Fig. 4. Evolution of pre-invasion stock levels.

Fig. 5 presents the time path of optimal preventive efforts under those same parameter sets. These scenarios differ both in the degree to which preventive efforts are used, and in how long they are maintained. Table 2 presents the constant optimal mitigation level chosen for each scenario.

In the case of a high biological growth rate, resilience clearly builds quickly because stock builds quickly. High preventive measures are therefore only necessary for a short period of time early in the time horizon; when resilience is high enough, preventive measures are stepped down. Among the remaining cases, resilience is built most quickly when there is a high policy-independent hazard rate; it makes intuitive sense that a system at greater risk of invasion would induce a more rapid development of a buffer against the effects of that invasion. This rapid build up is accompanied by very high preventive efforts that are again terminated when resilience reaches an appropriate level.

A similar pattern is observed when the marginal benefits of resource harvest are relatively high. The system protects current benefits through high preventive efforts and protects expected post-invasion benefits by quickly building system resilience. Because the increased incentive for harvest results in higher harvest and lower stocks, however, this accumulation of resistance occurs through high mitigative efforts rather than through maintenance of high stock levels.

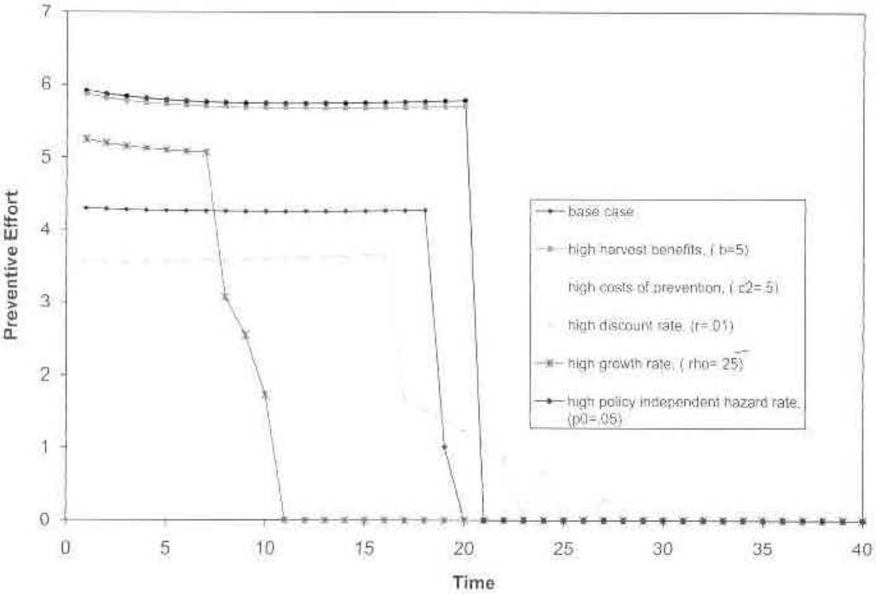

Fig. 5. Optimal paths of preventive effort.

Table 2
Optimal mitigative effort level when mitigative effort is assumed to be constant over the full time horizon

Scenario	Optimal mitigative effort level
Low mitigative cost	6.2
High policy independent hazard rate	5.1
High harvest benefits	4.7
High costs of prevention	2.6
Baseline scenario	2.2
High discount rate	1.65
High growth rate	1.55
High mitigative cost	.31

Relative to the other scenarios illustrated, the baseline scenario strategy uses a moderate level of preventive effort to shield the system while resilience is built at a moderate rate. This resilience is built through a mix of stock growth and mitigative effort, and approximately 20 years into the time horizon is sufficiently large for preventive efforts to be terminated.

As expected, the high discount rate effectively discounts the importance of system collapse by placing less importance on the future, which includes post-invasion impacts. This results in lower expenditure on preventive efforts, a slower rise in resilience through lower mitigative expenditures, and a lower eventual stock level. Due to this combination of factors, the system with a high discount rate approaches a resiliency level of 1 at a much slower rate than the other systems. However, also notice that preventive efforts are maintained longer, though at a relatively low level, when the discount rate is high. The slow rise in resiliency is somewhat compensated for by the prolonged maintenance of preventive efforts.

Some other results are also worth noting. The stock of resources follows its highest path, and settles to the highest steady-state stock level, when the costs of mitigative efforts are high. This again illustrates the substitutability between stock levels and mitigative effort in maintaining resiliency; when mitigative effort is expensive, more of the burden for maintaining ecosystem resilience is placed on the stock. The opposite effect is also true. When mitigative costs are low, stock levels are allowed to fall, and ecosystem resilience is maintained through higher mitigative efforts. As noted, a similar strategy holds when there are high benefits from harvest.

4. Conclusions

In this paper we examine the optimal allocation of preventive and mitigative efforts for an ecosystem hosting a renewable resource that is faced with threats from alien species invasion. Clearly, the existence of uncertainty in the timing and nature of an invasion has important implications for the optimal management strategy for the native system. There are two fundamental approaches available for managing the damage that could be caused by an alien species invasion: prevention of the arrival altogether, or mitigation of the impact of that arrival. The impact of the arrival can be mitigated using either stock management or manipulation of external ecosystem health. The combination of strategies that constitute the optimal management scenario in each case is determined by the relative cost-effectiveness of each of the policy instruments. Both the analytical and numerical results highlight the tradeoffs that exist between preventive and mitigative efforts, and between different forms of mitigative effort, in building and maintaining ecosystem resilience in such a system.

Several variables and relationships are illustrated to have implications for optimal resource management. These include, in particular, the effectiveness of preventive and mitigative instruments and the relationships between those instruments and their costs. One of the forms of mitigative efforts incorporated into the model is stock maintenance. The decision about whether to harvest the stock or to use it to build resilience in the system can be seen as a decision between current consumption and investment in future productivity of the system. In the absence of uncertainty about future productivity, the optimal stock level balances the marginal productivity of the stock against the opportunity cost of alternative investments (i.e. in the interest rate). In the presence of a stock-dependent mitigative effect, the optimal stock level is also sensitive to the expected growth rate of the difference between marginal benefits of current consumption of stock and the marginal benefits of future investment of stock. The latter factor is impacted by the effectiveness with which stock influences system resilience. These considerations add significant complexity to the system's behavior as parameters such as discount rate and risk of invasion are varied. Nevertheless, several key insights emerge.

Most importantly, the optimal management strategy for a system at risk of invasion depends on a combination of economic and biological factors and cannot be determined when these factors are considered in isolation. Clearly, when a full suite of alternative preventive and mitigative management options is available, the relative cost-effectiveness of policy instruments has important implications for allocating scarce resources toward combating invasive species. High preventive costs, for example, would lead to more stress on resiliency improving measures and thus would require some balance of a higher than usual level of stock and increased mitigative cost, depending on the relative costs. Those relative costs are sensitive to traditional economic considerations as well as to biological considerations such as the species' growth rate.

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Learning-by-catching: Uncertain invasive-species populations and the value of information

Sean T. D'Evelyn, Nori Tarui, Kimberly Burnett, James A. Roumasset*

Department of Economics, University of Hawaii, 2424 Maile Way, 542 Saunders Hall, Honolulu, HI 96822, USA

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Abstract

This paper develops a model of invasive species control when the species' population size is unknown. In the face of an uncertain population size, a resource manager's species-control efforts provide two potential benefits: (1) a direct benefit of possibly reducing the population of invasive species, and (2) an indirect benefit of information acquisition (due to learning about the population size, which reduces uncertainty). We provide a methodology that takes into account both of these benefits, and show how optimal management decisions are altered in the presence of the indirect benefit of learning. We then apply this methodology to the case of controlling the Brown Treesnake (*Boiga irregularis*) on the island of Saipan. We find that the indirect benefit—the value of information to reduce uncertainty—is likely to be quite large.

Keywords: Invasive species; Uncertain population; Learning; Value of information; Brown Treesnake

1. Introduction

An emerging problem in natural resource policy is how to design efficient strategies for managing invasive species.[1] Damages from invasive species are ecological as well as economic. These include lost biodiversity and reduced ecosystem services, as well as direct and indirect economic damages such as health damages or lost productivity. Caterpillars from the Asian gypsy moth (*Lymantria dispar*) cause extensive defoliation, reduced growth and mortality of host trees throughout the northern hemisphere, and hairs on larvae and egg masses lead to allergies in some people. The Nile perch (*Lates niloticus*) was introduced to Africa's Lake Victoria in 1954 and has since contributed to the extinction of more than 200 endemic fish species through predation and competition for food. *Caulerpa taxifolia* is a marine alga widely used as a decorative aquarium plant. The alga was accidentally introduced into the Mediterranean Sea in wastewater, where it has now spread over more than 13,000 ha of seabed. This invader forms dense monocultures that prevent the establishment of native seaweeds and exclude almost all marine life. Tamarisk (*Tamarix ramosissima*) is a shrubby tree that can be found where its roots reach the water table, such as floodplains, along irrigation ditches and on lake shores. Tamarisk can tolerate a wide range of saline or alkaline soils and is able to dominate floodplain communities in the deserts of the Southwest United States due to its ability to tolerate water stress for extended periods of time. Tamarisk supports few native insects and thus is poor habitat for birds.

The well-known invasion of the Brown Treesnake (*Boiga irregularis*) on the island of Guam poses a real and immediate threat to the state of Hawaii, due to the large and increasing volume of military transport between to the locales, as well as commercial air and sea traffic. The snake has extirpated 11 native bird species on Guam, causes hundreds of hours of power outages a year, and sends a stream of citizens to the hospitals each year to treat

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*Corresponding author. Tel.: +01 808 956 7496; fax: +01 808 956 4347.
E-mail address: jimr@hawaii.edu (J.A. Roumasset).

[1] Invasive species are defined as those plants, animals, and microbes that are nonnative to an area and have caused or have the potential to cause economic and or ecological damage threaten natural resources, biodiversity, and human health worldwide (from President Clinton's Executive Order 13112, signed February 3, 1999).

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venomous snakebites. Eight individual Brown Treesnakes (hereafter, BTS) have been intercepted at the ports in Hawaii, accompanied by hundreds of credible snake sightings resulting in zero captures.

While the economic literature on invasive species has been growing rapidly, most analyses are based on simplifying assumptions that limit their applicability. One aspect of invasive species control that makes practical implementation particularly difficult is that the actual population of the species is almost never known. The only variables that a typical resource manager observes with certainty are the number of the invasive successfully harvested and the effort required to achieve that harvest. Like most renewable resource problems, the literature to date typically assumes a given initial population of the stock of interest. In our paper we develop a model in which the invasive species population is known neither in the initial period nor in subsequent periods. Instead of setting harvest directly, managers set effort levels in each period and then observe the harvest.

In the context of renewable resource use, several studies have analyzed the case where the resource stock is uncertain due to lack of information or measurement error (Clark and Kirkwood, 1986; Roughgarden and Smith, 1996; Sethi et al., 2005). Economic studies of biological invasion have focused on the case of deterministic species population. Some studies analyze special cases where the optimal control under uncertainty is identical to that of the underlying deterministic model (Reed, 1979; Knowler, 2005). Recent studies analyze uncertain aspects of biological invasion more explicitly. Olson and Roy (2005) examine optimal prevention and control strategies for a randomly introduced biological invasion, assuming that prevention can be effective with certainty and that the population size is observable once invasion occurs. Saphores and Shogren (2005) allow growth to be uncertain, although stock is always accurately observed. We depart from these existing models on invasive species management by assuming uncertain species population size and allow for managers to adjust their subjective probability distributions of population according to catch.

Through species management, the managers obtain new information each period about the probability distribution of the species population size. Borrowing from the literature on renewable resources and learning, we model the connections between observable data (effort and harvest) and the unobservable invasive stock using Bayesian methods. If the effort-harvest function is stochastic but known, the model allows for beliefs about the invasive population to be updated each period and the manager is therefore able to tailor the control strategy appropriately.

Section 2 sets up the baseline case where the population is known with certainty. Section 3 outlines the optimal strategy when the population is uncertain and considers a simplified functional form to characterize the optimal solution. Section 4 illustrates the methodology for the case of BTS control on the island of Saipan. Section 5 concludes the paper with some suggestions for future research.

2. Method I: harvest with observable pest population

The usual renewable resource problem begins with a resource manager who maximizes the present value of a resource. Optimal management of an invasive species can be approached in a similar fashion. Maximizing the value of invasive species management is the same as minimizing the total present value of the expected costs of removing the species as well as the expected damages caused by the species.

In our model, the invasive species reproduces, causes damages, and is harvested in discrete time periods. We assume that population growth and ecological damages are deterministic, while the manager's harvest of the species is stochastic. The assumption of deterministic growth will help us isolate the information effects we are looking for later in the paper.

Let X_t denote the population of the invasive at time t. Each period this population causes $d(X_t)$ dollars worth of damage to the local ecosystem. Managers are able to reduce the population through stochastic harvesting. We denote e_t as the effort exerted to reduce the population, and $c(e_t)$ the cost the manager bears given e_t.

In the case where population is observable each period, the manager is able to set effort decisions based upon the observed harvest. The total present value (or cost, denoted PV) of the stock of the invasive, X, can be thought of as the optimal control costs today, the damages today, and then a discounted sum of the stream of control costs and damages into the future. We denote the discount factor as δ. The harvest in period t, h_t, is a function of the stock of the invasive X_t, the effort level e_t, and a random variable, ε_t.

$$h_t = h(X_t, e_t, \varepsilon_t). \qquad (1)$$

The variable ε represents the stochastic relationship between harvests, efforts, and population size. Future populations of the invasive will depend on the post harvest population and the species specific growth function, g:

$$X_{t+1} = g(X_t - h_t). \qquad (2)$$

The resource manager's objective is to maximize the discounted total expected present value of species management:

$$E\left\{\sum_{t=0}^{\infty} \delta^t(-c(e_t) - d(X_t))\right\}, \qquad (3)$$

subject to the harvest and species growth constraints (1) and (2) for all t given an initial population size $X_0>0$. Given this setup, the following functional equation for stochastic dynamic programming characterizes the optimal solution:

$$\mathrm{PV}(X_t) = \max_{e_t}\left\{-c(e_t) - d(X) + \delta E[\mathrm{PV}(X_{t+1})]\right\}, \qquad (4)$$

subject to (1) and (2) given an initial population size X_0. Efficiency requires that effort should be chosen so that the marginal cost of the effort is equal to the marginal benefit from reducing the population:

$$c'(e_t) = -E\left[\mathrm{PV}'(X_{t+1}|\varepsilon)g'(X_t - h_t)\frac{\partial h(X_t, e_t, \varepsilon)}{\partial e_t}\right]. \tag{5}$$

The left-hand side represents the marginal cost of efforts in period t. The right-hand side represents the expected marginal benefits of efforts in period t. Given ε, an increase in efforts changes harvests, which in turn influences the species growth and the species population next period. The right-hand side captures the resulting change in the expected present value of species control starting next period, where the expectation is taken over ε.

3. Method II: harvest under uncertain pest population

The above problem becomes more interesting and perhaps more realistic when the population of the invasive is not known with certainty. Managers in an uncertain world are no longer able to make policy decisions based on the true population of the invasive, but rather on estimates of those populations. Understandably, as the manager's estimate becomes more accurate, the closer the optimal policy resembles the solution when the population is known.

In the presence of uncertainty, a manager no longer has a simple population of the invasive that they must deal with, but instead is forced to optimize over the belief on uncertain population, i.e., a probability distribution of the possible population size. Every potential population size should be considered when determining the appropriate effort level.

Let F be the cumulative distribution function that the manager has over the population of the invasive. That is, $F(x) = P(X \leqslant x)$. Let f be the associated probability density function.

The following functional equation for stochastic dynamic programming characterizes the manager's maximization problem:

$$\mathrm{PV}(f_t) = \max_{e_t}\left\{-c(e_t) - \int_0^\infty f_t(x)\mathrm{d}(x)\,\mathrm{d}x + \delta E\left[\mathrm{PV}(f_{t+1})\right]\right\}. \tag{6}$$

In the presence of population uncertainty, the state variable is the probability density function over population size. That is, instead of the actual population, X, the present values are based on the probability distribution of possible populations and expected damages are used in place of actual damages. In what follows we describe how f_{t+1} is determined given f_t, effort e_t and observed harvest h_t.

3.1. Bayesian updating

Bayesian updating is a method of determining the distribution derived from previous beliefs and observable data. In this case, the harvest that the managers observe can be used directly in our Bayesian updating framework. First, let us define:

$$\tilde{x} \equiv h_t + g^{-1}(x), \tag{7}$$

or in other words, $\tilde{x}$ is the population last period that would yield a population of x this period. Now we can write

$$f_{t+1}(x|h_t, e_t, f_t(x)) = \frac{\pi(h_t|X_{t-1} = \tilde{x}, e_t)f_t(\tilde{x})}{\int_0^\infty \pi(h_t|X_{t-1} = x', e_t)f_t(x')\,\mathrm{d}x'}, \tag{8}$$

where π is the probability of observing a harvest of exactly h_t given population size $\tilde{x}$ and an effort level e_t.

Eqs. (6) and (8) together yield the necessary equations for maximizing the present value of the invasive under uncertainty. Since effort appears in the right-hand side of Eq. (8), effort will not only affect the expected mean of the population estimate next period, but may also affect the spread. When the posterior distribution given a harvest level is second-order stochastically dominated by the posterior given a lower harvest level, effort becomes more valuable than in the perfect certainty case. This extra value comes from the value of information.

3.2. A specific functional form

The equations presented in the last section describe how a resource manager would optimally determine the level of effort in each period. In order to provide a more precise understanding of how harvest and information updating work in this framework, we will add three simplifying assumptions to our model. First, we assume damages are linear in population. With this assumption we can set $d(X_t) = dX_t$ for all X_t. Second, we assume an exponential growth rate of the invasive, allowing us to write $g(X_t - h_t)$as $kX_t - kh_t$. Finally, we assume that control efforts are a binomial process, where each member of the population has an equal likelihood of being caught on a given round of treatment.

While these assumptions are not equally applicable to all invasive species, they can prove useful in a variety of settings. For example, while most managers agree that invasive species can cause massive economic damages, determining how much damage each individual member of the species causes can be a great challenge. For this reason, approximating damages as a linear function of the invasive population may be a reasonable estimate.

Not all species reproduce at an exponential rate. Resource economics typically assumes a logistic growth function, where the rate of growth slows as the population increases, to the point where annual growth rate declines past the point of maximum sustainable yield. However, invasive species introduced to a new ecosystem usually have ample supply of prey base and room to expand. The ability to rapidly multiply in number is one factor that makes invasive species such a problem in many cases, and makes an exponential growth function more reasonable.

Our most restrictive assumption is the availability of a binomial control strategy. In order for a control process to qualify it must have a repeatable methodology, with a likelihood of successful harvest of a given member in any iteration that is independent both of the harvest of other members of the population as well as independent of past control activities. This would exclude species where a large percentage of the population could be captured all at once (such as pack animals) or any control strategy that systematically cleared an area of the pest.

However, this approach is defendable for a wide variety of species, even ones that may not seem applicable. One example is that of sessile species such as the noxious weeds that threaten agriculture. If each sweep of an area is considered one round of the binomial event, so long as there is an imperfect chance of finding a given weed on a particular round, then frequency of the sweeps may depend on expected size of the population. For example, suppose a manager attempts to rid the managed area of spotted knapweed. The manager knows that it will be difficult to get 100% of the knapweed on the first sweep of the area. The assumption is that managers can capture a higher percentage of the knapweed with either repeated sweeps or more intense sweeps at the same effectiveness per person-hour.

As for animals that could potentially be caught at one time, thus violating the independence assumption, the problem can be alleviated by changing the unit of analysis. For example, red imported fire ants are likely to live together in anthills, and thus if one fire ant is discovered, it will be likely that a whole colony will be controlled. However, if the unit of analysis is moved to controlling anthills (or queen ants) then the harvest of each of those units are more likely to be independent of each other.

Effort in this context is a function of control techniques such as the number of snake traps set, concentration of toxicants, or simply person-hours spent hunting. These techniques are able to capture, trap, or otherwise kill a percentage of the invasive population in one period. Furthermore, varying either the frequency or the intensity of these techniques allows the manager to set different percent capture rates. It is these expected percent capture rates that we will call e in this context.[2] For example, an $e = .95$ would mean that the manager expected to capture 95% of the invasives whatever the optimal combination of control techniques necessary. The actual percent of the population captured varies around e_t, but harvesting can never add to the population nor can it remove more of a species than are actually present.

In addition to the plausibility and the analytical convenience explained above, this framework might be consistent with the decision making by the real world managers, who generally set effort levels for a given period and then simply harvest whatever that effort level yields. This setting is in contrast to many previous resource models where, even in the face of uncertainty, managers set a planned harvest level (or sometimes escapement level) and then merely observe whether or not that harvest depletes the population.

Given effort level e and population X, the probability that exactly h individuals are caught is given by

$$\frac{X!}{h!(X-h)!}e^{h}(1-e)^{X-h}. \tag{9}$$

However, this equation only works for discrete values of h and X. Where convenient we will use the continuous approximation of the binomial distribution. As X increases in size, and therefore as it approaches a continuous variable, the distribution of h becomes

$$h \sim N(e_t X_t, X_t e_t(1-e_t)). \tag{10}$$

Separating harvest into its deterministic and stochastic components, we have

$$h = e_t X_t + \varepsilon_t \quad \text{where } \varepsilon_t \sim N(0, X_t e_t(1-e_t)). \tag{11}$$

Let the expected proportion of the population controlled by a single unit of control effort be denoted α. If the effectiveness of each unit is independent, the expected proportion captured after n units are used is denoted:

$$e = (1-(1-\alpha)^n). \tag{12}$$

When characterizing the cost function, we assume that costs are linear in the control activities that determine e. If the cost per unit of the removal technique is c, then the cost of effort is

$$c(e_t) = \frac{c}{\log(1-\alpha)}\log(1-e_t) \equiv \theta \log(1-e_t). \tag{13}$$

Our problem can now be characterized by the following stochastic dynamic programming equation:

$$\mathrm{PV}(f_t) = \max_{e_t}\left\{-c(e_t) - \int_0^\infty f_t(x)d(x)\,\mathrm{d}x + \delta E\left[\mathrm{PV}(f_{t+1})\right]\right\}, \tag{14}$$

$$\hat{h}_t = X_t e_t(X_t) + \varepsilon_t, \tag{15}$$

$$h_t = \max\,(0, \min\,(\hat{h}_t, X_t)), \tag{16}$$

$$X_{t+1} = kX_t - kh_t, \tag{17}$$

$$\varepsilon \sim N(0, X_t e_t(1-e_t)), \tag{18}$$

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[2] We use expected capture rate as our measure of effort rather than the control technique itself, as is commonly done in resource economics (e.g., measuring effort as number of boats or person-hours). This allows the transition of population from one period to the next to simply be the previous population minus the proportion of snakes removed. Otherwise, the previous population would have to be reduced by a more complicated function of the control technique. For example, we would need to specify the precise relationship between the control technique and the number of individuals removed. In the case of snakes, for example, this would require specification of how many snakes would be removed through traps or search hours. Though this relationship still needs to be specified in our case, converting to capture rate simplifies the equation of motion. This substitution greatly facilitates computation in the case of harvest under uncertainty.

where $\hat{h}_t$ is potential harvest and the probability density function f_t is updated according to Eq. (8). Noting that $\hat{h}_t$ cannot exceed current population nor can it be negative), h_t is thus realized harvest.

A first-order necessary condition for efficient management in this problem is

$$\frac{\theta}{1-e_t}+\delta\frac{\partial E\left[\mathrm{PV}(f_{t+1})\right]}{\partial e_t}=0, \tag{19}$$

where the marginal cost of removal today must be equal to the present value of the change in damages and effort in later periods. This condition describes optimal effort, and thus control of an invasive species when harvesting under uncertainty.

3.3. Characterizing the optimal solution

If the harvest technique is a binomial process and the expected percent capture rates that efforts engenders are known, then the population can be estimated through the observed harvest and effort rates. We use the normal approximation for the binomial as given above wherever convenient.

If the manager has no prior knowledge about the stock of the invasive population at time $t=0$, after observing effort they can calculate

$$E[h_0]=E[e_0X_0+\varepsilon_0]=e_0E[X_0]. \tag{20}$$

Thus, after observing h and e, an unbiased estimate of X_t is given by

$$E[X_0]=\frac{h_0}{e_0}. \tag{21}$$

Note that Eq. (21) makes intuitive sense. If the manager expected to capture 50% of the population and then 100 species are successfully caught, a reasonable estimate for the total population would be 200. This estimate is approximately normally distributed with variance:

$$V[E[X_0]]=V\left[\frac{h_0}{e_0}\right]=\frac{1}{e_0^2}V[h_0]=\frac{X_0(1-e_0)}{e_0}. \tag{22}$$

This information is only somewhat useful in its current state, as population estimates at time t can only be obtained after the harvest for that time period takes place. However, since our growth function is known, we can use data gathered in the previous period to estimate the next period's population before any harvest decision is made. We define M_t as the pre-harvest estimate of X_t such that

$$M_1=E[X_1]=E[kX_0-kh_0]=k\frac{h_0}{e_0}-kh_0=kh_0\frac{1-e_0}{e_0}. \tag{23}$$

The variance of this estimate is:

$$V[M_1]=V[E[kX_0-kh_0]]=k^2V[E[X_0]]=\frac{k^2X_0(1-e_0)}{e_0}. \tag{24}$$

With this framework, we now have a means of deriving current population estimates from easily observable data. Unfortunately, the variance of these estimates does depend on the true stock size, an unknown parameter for the managers. In order to maintain normality and simplify our results, in our analysis we make the assumption that the managers know the variances of their estimates with certainty. Realistically, these variances would have to be estimated imprecisely, but would likely yield similar results.

Continuing with our example, we now have a pre-harvest expected population for period one. With this information, the manager is able to make a more informed decision for second period effort levels. However, after harvesting a second time, the manager could now form a second estimate for the population at time one from this new information. This new estimate can be written as

$$x_1=E[X_1]=\frac{h_1}{e_1}, \tag{25}$$

with variance

$$V[x_1]=E[X_1]=X_1(1-e_1)/e_1. \tag{26}$$

Except in very rare cases, this new estimate, x, will not equal the previous estimate of X_1. Because both of these estimates are normally distributed, obtaining the distribution for the most likely estimate for X_1 is straightforward. We first define ρ_t to be the precision of the estimate M_t equal to$1/V[M_t]$ and p to be the precision of our single period estimate x, equal to $1/V[x]$. Using these parameters, we can create a new estimate for X_1 that uses the available information to its fullest. As can be found in any elementary statistics book, the new estimate using both sets of information becomes

$$\frac{M_1\rho_1+x_1p_1}{\rho_1+p_1}, \tag{27}$$

where the variance is

$$\frac{1}{\rho_1+p_1}. \tag{28}$$

Generalizing this, and applying it to the problem of interest, the manager's problem becomes

$$\mathrm{PV}(M_t,\rho_t)=\max_{e_t}\{-\theta\log(1-e_t)-dM_t+\delta E[\mathrm{PV}(M_{t+1},\rho_{t-1})]\}, \tag{29}$$

$$\hat{h}_t=X_te(M_t,\rho_t)+\varepsilon_t, \tag{30}$$

$$h_t=\max(0,\min(\hat{h}_t,X_t)), \tag{31}$$

$$X_{t+1}=kX_t-kh_t, \tag{32}$$

$$\varepsilon\sim N(0,X_te_t(1-e_t)), \tag{33}$$

$$M_{t+1}=k\frac{(M_t-h_t)\rho_t+(x_t-h_t)p_t}{\rho_t+p_t}, \tag{34}$$

$$\rho_{t+1} = \frac{\rho_t + P_t}{k^2}, \tag{35}$$

$$x_t = \frac{h_t}{e_t}, \tag{36}$$

$$P_t = \frac{e_t}{X_t(1 - e_t)}, \tag{37}$$

where $\hat{h}_t$ and h_t are again potential and realized harvest as described in the previous section, X_{t+1} the new (uncertain) population, M_{t+1} the pre-harvest estimate of X_{t+1}, ρ_{t+1} the precision of the new pre-harvest estimate, x_t the estimate of the population using only harvest and effort in time t, and P_t the precision of this estimate.

In this uncertain framework, effort decisions can only be made based on the expected population M and the precision with which we can make that estimate, ρ. The present value is thus not only a function of the stock of the invasive, but also of the information held at time t. Our first-order equation now becomes

$$\frac{\theta}{1 - e_t} + \delta \frac{\mathrm{dE}[\mathrm{PV}(M_{t+1}, \rho_{t+1})]}{\mathrm{d}e_t} = 0 \tag{38}$$

or

$$\frac{-\theta}{1 - e_t} \approx -\delta k E[X_t \mathrm{PV}_1(M_{t+1}, \rho_{t+1})] + \frac{\delta}{k^2(1 - e_t)^2} E\left[\frac{\mathrm{PV}_2(M_{t+1}, \rho_{t+1})}{X_t}\right]. \tag{39}$$

The term $\mathrm{PV}_1(M_{t+1}, \rho_{t+1})$ refers to the partial derivative of the present value with respect to the first argument, M_{t+1}, and $\mathrm{PV}_2(M_{t+1}, \rho_{t+1})$ the partial derivative with respect to the second term, ρ_{t+1}. Expected values are taken both over all possible stocks of the invasive, X, and over all possible harvest levels, h, given X. The first term on the right-hand side of the equation is equivalent to the right-hand side of Eq. (19) and represents the marginal benefit from reducing the population in the next period.

Effort in the context of uncertainty now gains a secondary benefit. Not only does it reduce the expected population next period, but it also increases the precision with which the manager knows the population. The second term on the right-hand side of Eq. (39) represents the additional value gained from increasing the precision of the population estimate in the next period. The value of this term is the additional value above and beyond the damages avoided from removing the invasive species from the existing population, one almost always ignored in the literature to date.

4. Case study: BTS on the Island of Saipan

In order to illustrate the applicability of a population updating approach, we now turn to the case of the BTS on Saipan, located north of Guam in the Commonwealth of the Northern Mariana Islands. BTS has already been noted to cause extensive economic damage on Guam in the form of biodiversity losses, massive power outages, and health costs (Savidge, 1987; Fritts et al., 1987, 1990, 1994; Burnett et al., 2006). Because of the heavy military presence on Guam and its accompanying movement of people and cargo off island, BTS threatens surrounding islands in the Pacific. A recent estimate of an optimally managed BTS population in Hawaii, for example, approaches $18 million dollars (Burnett, 2007). Although Guam authorities have tried vigilantly to minimize the chance of BTS escaping to other islands, Saipan has had several sightings of BTS, and program scientists and managers believe there is an incipient population (Nathanial Hawley, personal communication).

Based on data gathered on Guam, the cost to sweep the island looking for snakes enough times to obtain an expected percent capture rate of e is: -$2,023,000$*\log(1-e)$. For a more detailed look at the derivation of this formula, see the appendix. Assuming that BTS will cause similar damages to Saipan as it might in Hawaii, we estimate d to be 121.79 per year or approximately $10.15 per month[3]. Since prey base is likely to also be similar to that of Guam, we estimate a per month growth rate of 1.0399, and we set a monthly discount rate of 1.00165, which is equivalent to an annual discount rate of 2%.

Conversations with invasive species managers suggest that there is a small incipient population of BTS on Saipan. There have been 75 credible sightings of BTS on island, leading to zero captures. While it is possible that all 75 sightings could be due to a single snake, this is highly unlikely. For the purposes of this example, we suppose that the manager estimates that there are about 200 snakes, with a standard deviation of 100 (and therefore a precision of .0001). Even if the true population is drastically different from 200, the updating process will quickly yield a better estimate.

In order to illustrate the effects of learning on the optimal species management, we conducted a Monte Carlo simulation and compared two strategies—one with learning (S^L) and the other without learning (S^N). With strategy S^L, the manager updates its belief on the probability distribution of the population size based on efforts and observed harvests. Strategy S^N assumes that the manager chooses efforts in each period based on the initial belief about the species distribution without updating the belief over time.

We assume the same initial belief about the distribution of population size:

$$X_0 \sim N(M_0, 1/\rho_0),$$

where (M_0, ρ_0) is specified as in the above section. Under strategy S^N, the manager chooses

$$e_t^N = \max\left\{0, 1 - \frac{X^*}{kM_t}\right\}, \quad t = 0, 1, 2, \ldots, T, \tag{40}$$

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[3] See Burnett (2007) for a detailed description of damage estimations.

where X^* represents the steady-state species population size in the deterministic version of the model (where the initial population is given by M_0) and where

$$M_{t+1} = kM_t(1 - e_t^N), \quad t = 0, 1, 2, \ldots, T, \tag{41}$$

given M_0.[4] Strategy S^N is the optimal solution for the deterministic case ($M_t \equiv X_t$, $\rho = +\infty$, $\varepsilon_t \equiv 0$). The true population dynamics follows Eqs. (30)–(33) where e_t is replaced by e_t^N.

Under strategy S^L, the manager chooses

$$e_t^l = \max\left\{0, 1 - \frac{X^*}{kM_t}\right\}, \quad t = 0, 1, 2, \ldots, T, \tag{42}$$

where the mean and the precision (M_t, ρ_t) are updated according to the Bayes rule described in Eqs. (34), and (35). Though this strategy with learning is not necessarily the optimal solution to the species management problem (29)–(37), it incorporates learning in a simple and practically relevant manner.[5] Given the resource managers' information and costs constraints, a relatively simple strategy such as S^L might be implemented more easily than an optimal strategy.

We set the time horizon T to be 240 (i.e., 20 years), and computed the present values of species control under the two strategies by running 1000 replications. We evaluate the outcome of each trial using the social costs of invasive species management, i.e., the present value of the sum of control costs and damages due to invasion given the realization of initial population size, with and without learning. Let SC_n^L and SC_n^N be the realized social costs with and without learning under the nth replication (trial):

$$\mathrm{SC}_n^J = \sum_{t=0}^{T} \delta^t \{-c(e_t^J(n)) - d(X_t^J(n))\}, \quad J = L, N.$$

Let $\overline{\mathrm{SC}}^L$ and $\overline{\mathrm{SC}}^N$ be the average of social costs over all trials $n = 1, \ldots, T$. The difference between $\overline{\mathrm{SC}}^L$ and $\overline{\mathrm{SC}}^N$ indicates the expected value of information.

Out of 1000 trials, SC^L exceeded SC^N only 41 times. The 1000 trials yielded the averages $\overline{\mathrm{SC}}^L = \$13.6$ million with learning and $\overline{\mathrm{SC}}^N = \$78.9$ million without learning—or about 6 times as large as $\overline{\mathrm{SC}}^L$. This experiment implies that the value of information through species control can be substantial. Under learning, updated information allows the managers to change the flexibly of control efforts. Such flexible updating allows the manager to achieve a smaller expected social cost.

Figs. 1 and 2 describe the population dynamics and the effort profiles for two illustrative trials. In each figure, the top panel describes the true species population dynamics while the bottom panel shows the time profile of effort. In both cases, the effort profile with learning fluctuates constantly while the effort profile without learning is monotonic over time. This is because, under learning, the probability distribution of population is constantly updated. During periods of high and low catch, the estimated population adjusts up and down accordingly, triggering a higher (lower) effort level in the next period. In contrast, the effort profile without learning is monotonic because the estimated population remains unchanged. Fig. 1 plots a scenario where strategy S^N resulted in extinction while strategy S^L caused the population size to fluctuate around $X^* = 329$, the optimal steady state for the deterministic version of the model. Despite species extinction, S^N resulted in a higher social cost (8% larger than SC^L) due to an excess of control costs resulting from the manager failing to learn about the diminished population. Fig. 2 demonstrates a contrasting case wherein control without learning results in insufficient effort and an explosion of the pest population. In this trial, SC^N was about 540% larger than SC^L.[6] Together, the two figures demonstrate that

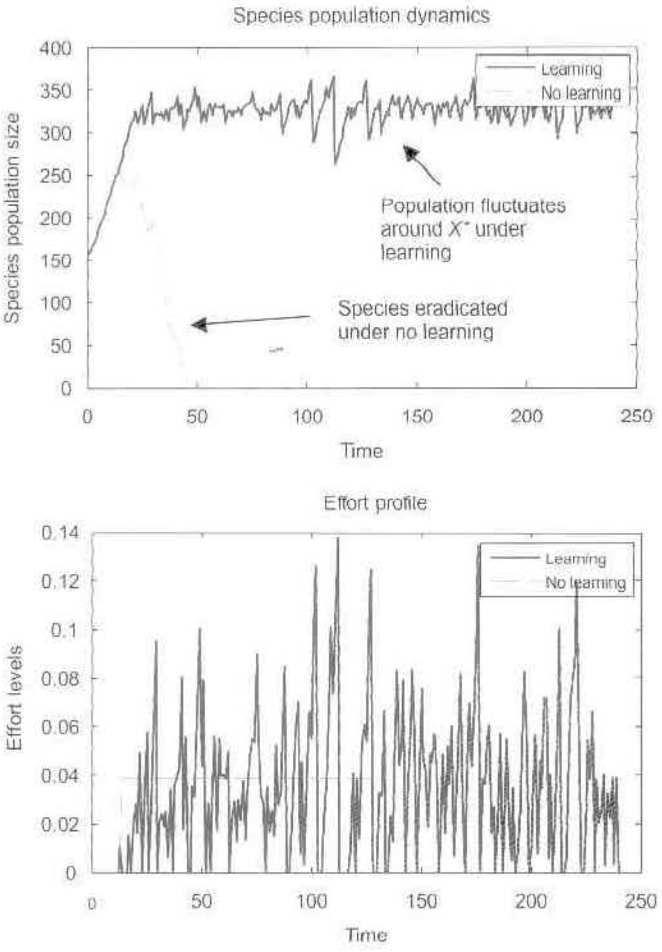

Fig. 1. Species population dynamics and effort: case 1

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[4] Given the parameter values specified in the previous section, X^* equals 329.

[5] The effort decision in Eq. (43) is an example of "constant escapement policy." When a constant escapement policy is optimal in a deterministic resource-use model, it is not necessarily optimal in the same model with uncertainty (Clark and Kirkwood, 1986; Sethi, et al., 2005). For conditions under which equivalence obtains, see Reed (1979).

[6] This large number is due to the assumption that, without learning, the manager does not update her belief about the population, even if the population explodes. This assumption is standard in the value-of-information literature, and may be a reasonable baseline case for valuing

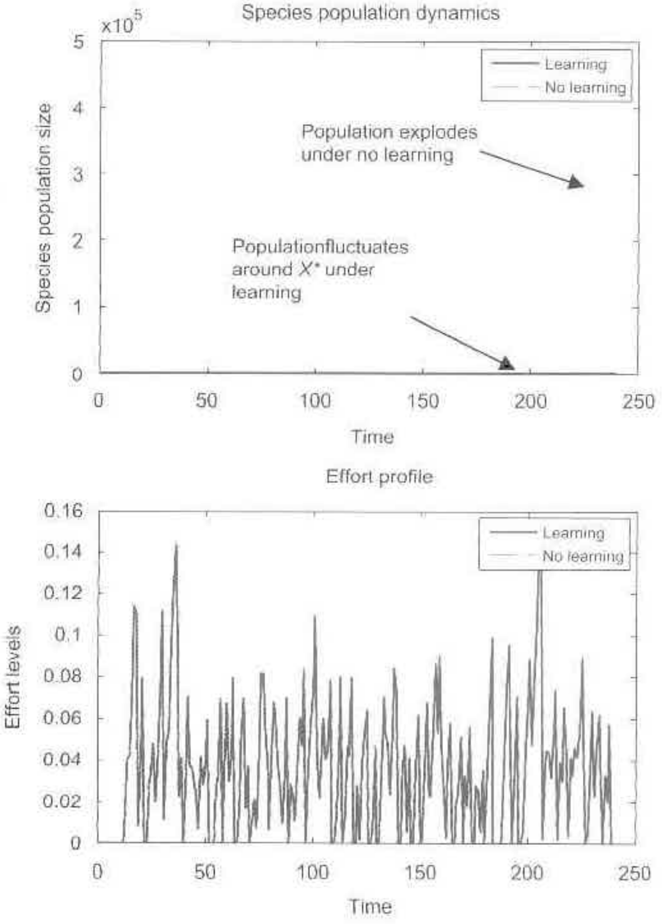

Fig. 2. Species population dynamics and effort: case II

failure to learn may result in control efforts that are too high or too low. These two trials imply that, given exponential growth of an unchecked pest population, the cost of applying insufficient control efforts is much larger in magnitude than the cost of applying excessive control efforts relative to what Bayesian learning indicates.

5. Discussion and conclusion

Optimal management of an invasive species is challenging when the actual population being controlled is uncertain. How should resource managers take account of existing information about population size and invest in learning about that size? In this paper, we develop a framework to solve for optimal invasive species management where the resource manager can update their subjective belief about species population using Bayesian methods. When effort spent on controlling the population not only lowers future expected population but also provides the manager with more precise estimates for the future, early control efforts become even more important than in models where invasive populations are known. This result is derived analytically and illustrated numerically.

By comparing the average present values of invasive species management with and without learning, we can compute the value of additional information due to learning. We parameterize our model to analyze BTS control in Saipan and estimate the value of information. A Monte Carlo simulation indicates that learning reduces the cost of species control and damages in almost all cases. In Section 4 we showed the result of two trials where, in the absence of learning, one resulted in excessive control efforts and costly species eradication while the other resulted in insufficient control efforts and species population explosion. On average, the social cost with learning was only $\frac{1}{6}$ of the cost without learning. Costs are especially high in the case where the population has been underestimated and where the population grows rapidly in the face of under-control. The value of learning will be lower if the planner merely delays adjusting the control efforts upwards but substantial nonetheless. These results suggest that a traditional framework to analyze biological invasion given deterministic species population will not provide efficient management strategies, and that the value of information due to learning can be large.

The model developed in this paper can be extended in a number of directions. Population estimation through stochastic harvesting processes is useful in any setting, but it is even more useful when either growth is uncertain or when the populations are subject to random shocks (e.g. due to new invasions, a new food source, disease, or a new predator). While estimation techniques doubtlessly become less precise in such cases, continual updating of the population is even more important. Another extension could allow for heterogeneity in catchability, such that the more easily caught tend to be caught earlier. This would imply a role for learning about the efficacy of control techniques as well as learning about the size of the population. Analysis of these issues is left for future research.

Acknowledgments

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Appendix A. : Cost of removal

In a recent study, Gordon Rodda of US Geological Survey examined the catchability of snakes on a 5 ha enclosed plot in Guam. Although a large degree of

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(footnote continued)
information in other contexts such as weather forecasting (e.g., Costello et al., 1998). In the context of invasive species management with exponential population growth, this assumption of a naïve resource manager might not be realistic. At some point, the manager is likely to learn that her population beliefs are wrong, but when? Several scenarios can be considered, but see Burnett et al.'s (2007) demonstration in another context that the losses from delayed correction of status quo policies (as opposed to no correction) are still large. Note also that in the 568 in which social costs of failing to learn are modest (because the population is actually declining) the value of learning is still 17%.

individual heterogeneity was found. BTS in the experiment had an average of a 16.36% chance of being caught on a given night of trapping. Saipan is approximately 12,043 ha in area, all of which is potential snake habitat. With the aid of Gordon Rodda, we estimate the cost per night of trapping per 5 ha plot to be around \$150. Thus, using the definition of θ, above, our costs of effort on Saipan will be

$$\frac{12,043\,\text{ha}}{5\,\text{ha/plot}} * \$150/plot * \frac{1}{\log(.163564)} * \log(1-e) \approx -\$2,023,177\,\log(1-e). \tag{43}$$

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Robust detection protocols for uncertain introductions of invasive species

L. Joe Moffitt[a,*], John K. Stranlund[a], Craig D. Osteen[b]

[a]Department of Resource Economics, University of Massachusetts, 212B Stockbridge Hall, 80 Campus Center Way, Amherst, MA 01003-9246, USA
[b]USDA Economic Research Service, Washington, DC, USA

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Abstract

Two important features of real-world port inspections of shipping containers for invasive species are the general absence of underlying economic considerations and the climate of severe uncertainty that surrounds the likelihood of invasive species introductions. In this article we propose and illustrate a method for determining inspection protocols that address both of these issues. We seek inspection protocols that are robust in the sense that they maximize the range of uncertainty over which the expected loss from the introduction of an invasive species plus the costs of inspections do not exceed some critical value. These inspection strategies are practical and provide ready alternatives to existing protocols.

Keywords: Invasive Species; Inspections; Uncertainty; Robustness

1. Introduction

Approaches to managing invasive species problems include preemptive actions against potential invaders in foreign locales, border activities such as inspections to prevent introductions across international boundaries, domestic monitoring and control to prevent establishment if introductions occur, management of domestically established introductions through use of various forms of interference (e.g., vector control, enemies, pathogens, symbionts, endophytes, hosts, and/or physical factors perhaps as part of area wide management programs), and combinations of these approaches.

This paper focuses on inspection protocols. Current practice for inspecting cargo shipments of fruits and vegetables at US ports is based on inspecting a small percentage (2%) of the items in a container for the presence of pests, with some allowances for the size, contents, and origin of the container.[1] Clearly, this decision rule has no economic content. Thus, the rule determines the number of items in a container to be inspected without considering the costs of inspections and the losses of failing to prevent an invasive species from entering the country. In this paper, we propose a decision criterion that incorporates these values.

With these data and known, or confidently estimated, probability distribution functions over the place and timing of invasive species introductions, one could cast the problem of determining optimal inspection protocols in the familiar terms of risk analysis. However, in many areas of economic decision making, including the management of invasive species, it is often difficult to measure and interpret probability distributions associated with uncontrolled events; consequently, concerns about the usefulness of risk assessment are evident among researchers and practitioners alike (Moffitt and Osteen, 2006).

What this strongly suggests is that it may not be useful to think about determining inspection protocols for invasive species as decisions involving gambles with known

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*Corresponding author. Tel.: +1 413 545 5719; fax: +1 413 545 5853
E-mail address: moffitt@resecon.umass.edu (L. Joe Moffitt).

[1] From United States Department of Agriculture, Animal and Plant Health Inspection Service, *Regulating the Importation of Fresh Fruits and Vegetables*. ⟨http://www.aphis.usda.gov/ppq/manuals/port/FV_Chapters.htm⟩. Accessed last on November 8, 2006.

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probabilities. Instead, we are truly in a world of Knightian uncertainty; that is, not only are we ignorant about potential invasive species introductions, we are also ignorant of the likelihood of these introductions.[2] Thus, decision criteria for determining inspection strategies for shipping containers must account for this uncertainty.

Several approaches have been developed to analyze decision making under true uncertainty. These approaches include application of the maximin, maximax, Laplace, and Hurwitz criteria (Render et al., 2006). While none of these criteria require knowledge of probability distributions for application, the first two represent polar extremes in terms of optimism and pessimism while the latter two require information similar to probabilities in order to be applied. Similarly, quantification of other notions related to uncertainty such as ignorance and surprise has also required the specification of functions confined to the unit interval (Katzner, 1998; Horan et al., 2002).

Some recent decision theory research has focused on the notion of robustness in decision making as a means of coping with uncertainty. Ben-Haim (2006) has developed a new approach to decision making under uncertainty known as information-gap (info-gap) decision theory, which he designed for cases in which probability distributions for uncontrolled events are not available. The essence of info-gap analysis is the pursuit of decisions that are robust in the sense that they maximize the range of uncertainty about model parameters within which the decision maker is certain to achieve a specified performance criterion. One decision is more robust than another if the range of uncertainty under which the performance criterion is met is larger.[3]

We adopt Ben-Haim's approach to the problem of determining robust inspection protocols for detecting invasive species in shipping containers. In this problem we are uncertain about the likelihood of the presence of an invasive species in a container, but we seek a robust inspection protocol to maximize the range of this uncertainty over which the expected loss from an introduction plus the costs of inspections will not exceed some critical value. This approach provides a way of determining robust inspections strategies in the invasive species realm that incorporates economic considerations, true uncertainty, and is free of subjective probability assessment and its time-consuming, costly, and questionable practices (Ouchi, 2004).

2. The model: robust inspection protocols

A container subject to inspection at a port of entry contains N items. Inspection of $n \leqslant N$ of the items for the presence of invasive species will occur to determine if the container is approved for entry. If an item is inspected, then it will be known with certainty whether or not the item plays host, even if perhaps only temporarily, to an invasive species. If an invasive species is detected on any item in the container, then the container is refused entry possibly pending actions outside the regular inspection protocol, such as treatment or destruction. The costs of inspecting n items is $c(n)$, which is increasing in the number of inspected items.

Suppose that $s \leqslant N$ items in the container are infested, but that the value of s is completely uncertain. The inspection process fails if it does not detect any infested items and entry is allowed when at least one item in the container is infested. The probability of failure of the inspection process, denoted by π, is given by the ratio of binomial coefficients

$$\pi(s, n, N) = \binom{N-s}{n} \Big/ \binom{N}{n}; \tag{1}$$

that is, the failure probability is the ratio of the number of possible samples of size n which do not contain an infested item to the total number of possible samples of size n. It is straightforward to demonstrate that this failure probability is decreasing in the number of infested items; that is, given n inspected items out of N in a container, the probability that an infested item is not detected is larger when the number of infested items is small. Obviously, given s infested items in a container with N items, inspecting more of the items in the container reduces the failure probability.

Our approach to determining robust inspection protocols incorporates the costs of failing to prevent an invasive species from entering a country and the costs of inspections. Entry of any infested item is assumed to cause a certain loss L, so the expected loss due to entry of an undetected pest is $L\pi(s, n, N)$.[4] In this section and the next one, we assume that L is independent of the number of infested items that get through the inspection protocol.[5] In

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[2] Knight was concerned "with situations which are far too unique, generally speaking, for any sort of statistical tabulation to have any value for guidance. The conception of an objectively measurable probability or chance is simply inapplicable." Knight referred to this as true or unmeasurable uncertainty (Knight, 1921, Chapter 7).

[3] Ben-Haim's decision theory has been applied to a wide variety of problems, including financial risk assessment (Ben-Haim, 2005), search behavior in animal foraging models (Carmel and Ben-Haim, 2005), policy decisions in marine reserve design (Halpern et al., 2006), natural resource conservation decisions (Moilanen and Wintle, 2006), inspection decisions by port authorities to detect terrorist weapons (Moffitt et al., 2005) and invasive species (Moffitt et al., 2007), technological fault diagnosis (Pierce et al., 2006) and engineering model-testing (Vinot et al., 2005).

[4] There are likely to be random elements of the damage caused by an invasive species introduction, and these elements may even be truly uncertain. We assume that this loss is known with certainty in order to focus on one uncertain element, that is, on the number of infested items in a container. Our approach is easily modified to account for uncertain damage from invasive species introductions.

[5] While perhaps not strictly true in all cases, for invasive species of major concern; i.e., mobile pests with a wide host range who find the climate suitable for reproduction, this assumption will not be unduly restrictive. In such cases, the absolute number of undetected invaders will not, aside from timing, alter the ultimate impact.

Section 4 we allow the loss to increase with the number of undetected invaders.

In general, robustness is the maximum range of uncertainty over which a performance criterion is met. Since we are uncertain about the number of infested items in a container, we define robustness with respect to s. The performance criterion is that the expected loss from failing to detect an infested item plus the cost of inspections do not exceed a critical cost value L_c. Formally, given n of N inspected items, robustness is the solution to

$$\max_{s\in[0,N]} L\pi(s,n,N)+c(n)\leq L_c. \tag{2}$$

Since, given n and N, the failure probability is decreasing in s, the solution to (2) is the least s for which the inequality is satisfied. Denote this solution as $s(n, N, L_c)$. If the actual number of infested items is greater than $s(n, N, L_c)$, then the expected loss from an undetected infestation plus the costs of inspections are less than the critical value L_c. If the number of infested items is less than $s(n, N, L_c)$, then the expected loss from an undetected infestation plus the costs of inspections are greater than the critical value L_c. More succinctly, given that n items are inspected, society is immune to experiencing expected cost L_c if and only if the actual number of infested items is greater than $s(n, N, L_c)$.

A robust inspection protocol then is the number of inspected items that minimizes $s(n, N, L_c)$, because doing so provides the maximum range of the uncertain number of infested items within which society is immune to L_c. Therefore, the robustness maximizing number of items to inspect in a container with N items is

$$n(N,L_c)=\arg\min\nolimits_n s(n,N,L_c), \tag{3}$$

and the minimum number of infested items for which society is immune to L_c is

$$s(n(N,L_c),N,L_c)=s(N,L_c). \tag{4}$$

3. A numerical illustration

Application of our approach is illustrated by considering inspection effort for containerized agricultural cargo requiring inspection prior to entry into a country. Tables 1 and 2 provide robust inspections and robustness measures, respectively, for alternative numbers of containerized items and performance criteria. Our analysis considers a container with fruit and vegetable items, such as boxes or crates, where the number of such items is permitted to range from 250 to 2500 in 250 item intervals (Tables 1 and 2, column 1). It is assumed that the number of items infested with a deleterious invader is completely unknown. For item numbers in this range, the current rule of inspecting 2% of the items in a container requires inspection of 5–50 items in 5 item intervals (Tables 1 and 2, column 2). To determine the optimal robust inspection effort given by (3), we assume that failure to detect an invasive species among items in the cargo results in a \$10 million loss. In addition, the cost for inspecting n items is $c(n)=1000\text{–}2000n+1000n^2$. Note that this cost function is increasing and strictly convex for $n>1$ and thus features anticipated cost function properties.

We also consider alternative performance criteria, L_c, ranging from \$0.5 million to \$5 million in \$0.5 million increments (Tables 1 and 2, row 1). Optimal robust inspections given in Table 1 were determined according to (3) as the solution to a series of constrained integer programming problems corresponding to alternative cargo sizes as measured by number of like items in the shipment and alternative performance requirements.[6]

Table 2 provides two measures of robustness. Each cell in the table contains two values: the top value is the minimum number of infested items for which the performance criterion is met—$s(N, L_c)$ from equation (4)—while the bottom value is the corresponding minimum percentage of infested items, $100\times s(N, L_c)/N$, which is helpful in interpreting the results. For comparison to current practice, column 2 in Table 2 provides these robustness measures for the current 2% rule evaluated at the critical cost value $L_c=\$2.5$ million.

Let us first examine the robust inspection strategies in Table 1. Perhaps the most important message of these data is that robust inspection strategies are very different from the "2% inspection benchmark," or for any other fixed-percentage rule for that matter. Obviously, any fixed-percentage rule requires that the number of inspected items increases monotonically with the number of items in a container. For example, with the 2% rule, inspected items increase from 5 for a container of 250 items to 50 for a container of 2500 items. However, for a given performance criterion there is not nearly as much variability in robust inspections, nor are these inspections necessarily increasing as N increases. For example, when the performance criterion is to limit expected invasive species losses plus inspection costs to $L_c=\$5$ million, the number of inspected items varies from a high of 48 for a container with 250 items to a low of 40 items inspected in a container of 2500 items.

Also note the tendency for robust inspections to be greater than 2% when the number of items in a container is low, and to be less than 2% when the number of items is high. For example, when the performance criterion is $L_c=\$2.5$ million, the robust number of inspected items is higher than 2% for containers containing 1500 items or less, but is less than 2% for containers containing 1750 or more items. This high/low result is due to the lack of

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[6] The optimization was accomplished using *Mathematica* with its native routine for evaluating the binomial coefficients in the performance requirement along with integer constraints imposed on inspection effort, $n(N, L_c)$, and number of infested items, $s(N, L_c)$. The maximization of robustness according to (3) is a challenging optimization problem and, not surprisingly, one that is characterized by multiple optimal solutions due to the presence of the integer constraints on the choice variables. Even so, the alternative integer values of $n(N, L_c)$ which corresponded to the optimal level of $s(N, L_c)$ were generally found to be in quite close proximity to one another.

Table 1
Robust inspection strategies, $n(N, L_c)$

Number of items (N)	2% inspection benchmark	Performance criterion (L_c)									
		0.5×10^6	1.0×10^6	1.5×10^6	2.0×10^6	2.5×10^6	3.0×10^6	3.5×10^6	4.0×10^6	4.5×10^6	5.0×10^6
250	5	20	23	27	33	38	37	40	40	46	48
500	10	18	25	32	34	37	44	40	37	48	41
750	15	19	27	30	33	37	38	41	41	43	43
1000	20	19	25	31	34	37	39	41	44	48	45
1250	25	19	26	30	34	36	40	40	41	47	42
1500	30	19	25	31	34	35	39	39	41	42	44
1750	35	19	26	29	34	36	39	42	45	41	42
2000	40	19	26	31	34	35	37	38	42	43	44
2250	45	19	26	30	34	37	39	39	41	45	41
2500	50	19	25	31	34	34	39	43	43	43	40

Table 2
The minimum number of infested items for which a performance criterion is satisfied, $s(N, L_c)$, and the corresponding minimum percentage of infested items, $100\times s(N, L_c)/N$

Number of items (N)	2% inspection benchmark[a]	Performance criterion (L_c)									
		0.5×10^6	1.0×10^6	1.5×10^6	2.0×10^6	2.5×10^6	3.0×10^6	3.5×10^6	4.0×10^6	4.5×10^6	5.0×10^6
250	61 (24.4%)	47 (18.8%)	29 (11.6%)	21 (8.4%)	16 (6.4%)	13 (5.2%)	11 (4.4%)	10 (4.0%)	8 (3.2%)	7 (2.8%)	6 (2.4%)
500	66 (13.2%)	95 (19.0%)	58 (11.6%)	43 (8.6%)	33 (6.6%)	27 (5.4%)	23 (4.6%)	20 (4.0%)	17 (3.4%)	15 (3.0%)	13 (2.6%)
750	70 (9.3%)	142 (18.9%)	88 (11.7%)	64 (8.5%)	50 (6.7%)	41 (5.5%)	35 (4.7%)	29 (3.9%)	25 (3.3%)	22 (2.9%)	19 (2.5%)
1000	74 (7.4%)	190 (19.0%)	118 (11.8%)	86 (8.6%)	67 (6.7%)	55 (5.5%)	46 (4.6%)	39 (3.9%)	34 (3.4%)	30 (3.0%)	26 (2.6%)
1250	79 (6.3%)	238 (19.0%)	147 (11.8%)	108 (8.6%)	84 (6.7%)	69 (5.5%)	58 (4.6%)	49 (3.9%)	43 (3.4%)	37 (3.0%)	32 (2.6%)
1500	87 (5.8%)	286 (19.1%)	177 (11.8%)	129 (8.6%)	101 (6.7%)	83 (5.5%)	69 (4.6%)	59 (3.9%)	51 (3.4%)	44 (2.9%)	39 (2.6%)
1750	97 (5.5%)	334 (19.1%)	207 (11.8%)	151 (8.6%)	118 (6.7%)	97 (5.5%)	81 (4.6%)	69 (3.9%)	60 (3.4%)	52 (3.0%)	45 (2.6%)
2000	112 (5.6%)	382 (19.1%)	236 (11.8%)	173 (8.7%)	135 (6.8%)	111 (5.6%)	93 (4.7%)	79 (4.0%)	68 (3.4%)	59 (3.0%)	52 (2.6%)
2250	138 (6.1%)	430 (19.1%)	266 (11.8%)	194 (8.6%)	152 (6.8%)	125 (5.6%)	104 (4.6%)	89 (4.0%)	77 (3.4%)	67 (3.0%)	58 (2.6%)
2500	219 (8.8%)	478 (19.1%)	296 (11.8%)	216 (8.6%)	169 (6.8%)	139 (5.6%)	116 (4.6%)	99 (4.0%)	85 (3.4%)	74 (3.0%)	65 (2.6%)

[a] Evaluated at $L_c = 2.5\times10^6$.

variation of robust inspections as N changes and the parameters we have chosen for this illustration. In other settings with different values for the loss from an introduction and the costs of inspections, robust inspections can be always higher or always lower than 2% inspections.

Finally, note that for a given number of items in a container, there is a general tendency for the number of robust inspections to increase as L_c is increased, although this relationship is not monotonic. As the performance criterion is relaxed so that the decision maker is willing to tolerate higher expected costs, more resources are devoted to increasing the number of inspected items.

Now let us turn to the robustness measures provided in Table 2. To recall how these values are interpreted, take the values associated with $N = 250$ items and $L_c = \$0.5$ million. In this case, the minimum number of infested items in a container with 250 items for which the expected loss from failing to stop a potential invasive plus the costs of inspections is 47. If the actual number of infested items in this container is less than 47, then the expected loss plus inspection costs will exceed $L_c = \$0.5$ million. However, the expected loss plus inspection costs will fall below \$0.5 million if the number of infested items is 47 or higher. In other words, society is immune to the critical cost $L_c = \$0.5$ million as long as the number of infested items is not less than 47. Moreover, 47 infested items implies an 18.8% infestation rate. Thus, society is immune to $L_c = \$0.5$ million as long as the percentage of infested items is not less than 18.8%.

Reading across the rows in Table 2 reveals a fundamental tradeoff in problems of this sort: that is, given robust decisions, society achieves greater immunity to loss only if it is willing to tolerate higher losses. For a particular container size, this is illustrated by $s(N, L_c)$ and $s(N, L_c)/N$ decreasing in L_c, implying greater robustness as the performance criterion is relaxed. To illustrate for a container with 1000 items, the minimum number of infested items for which the performance criterion is met steadily decreases from 74 items when the performance criterion is $L_c = \$0.5$ million to 26 items when the performance criterion is $L_c = \$5$ million. Correspondingly, the minimum percentage of infested items decreases from 19.0% to 2.6%.

For a given performance criterion, however, the minimum number of infested items always increases monotonically as the number of items in a container is increased. For example, for $L_c = \$0.5$ million, $s(N, L_c)$ increases monotonically from 47 in a container of 250 items to 478 in a container with 2500 items. Note, however, that for each performance criterion the minimum percentage of infested items for which the criterion is met is essentially constant as N increases. Thus, for $L_c = \$0.5$ million the minimum percentage of infested items is always about 19.0%. Recall from the robust inspection strategies in Table 1 that, given a performance criterion, there is little variation in the number of inspected items as N increases. Thus, it appears, in this example at least, that maximizing robustness to a particular performance criterion calls for an inspection strategy that maintains an essentially constant minimum percentage of infested items for which the performance criterion is satisfied.

Contrast this result to the robustness of the 2% inspection benchmark. The second column of Table 2 contains the robustness measures of the 2% inspection benchmark, evaluated at the performance criterion $L_c = \$2.5$ million. Although the minimum number of infested items increases as the number of items increases, the minimum percentage of infested item falls from 24.4% for a container of 250 items to 5.5% for containers with 1750 items and then increases as N continues to increase.

More importantly, though, the 2% rule is not maximally robust. Comparing the robustness measures of the 2% rule to those derived from the robust inspection strategies for $L_c = \$2.5$ million indicates that the 2% rule can never be more robust, and may be significantly less robust than the optimally robust decisions. This, of course, is what one would expect given the design of robust inspection strategies, but it does illustrate the difference between a rather naive fixed-percentage inspection rule and a strategy that simultaneously accounts for the economic values associated with preventing and failing to prevent introductions of invasive species and the severe uncertainty associated with this threat.

4. Robust protocols with infestation-dependent loss

While the model and illustrations shown in preceding sections seem most appropriate with respect to current inspection protocols in the United States and the characteristics of perhaps many potential invasive species, for other invasive species inspection failure may result in losses that depend on the number of infested items that get through the inspection protocol. For example, an invasive species with limited mobility and a wide host range might be best modeled in this manner. We call this characteristic of some invasive species introductions *infestation-dependent loss*, and modify our model in this section to account for this feature.

We maintain our model of inspection failure from the previous section, because this is consistent with current inspection protocols in the United States. That is, detection of any infested items will route a container outside the regular inspection process to receive special scrutiny, treatment, or destruction. Thus, inspection failure occurs when some items in a container are infested, but none of these are detected, the probability of which is $\pi(s, n, N)$ given by (1). In this section we define the loss from inspection failure to be not just a constant amount L as in preceding sections, but rather the infestation-dependent loss $L(s)$, which depends on the number of infested items in a container that passes through the inspection protocol. The expected loss from an invasive species introduction is then $L(s)\pi(s, n, N)$.

Recall that robustness, given n inspections, is defined as the number of infested items for which the expected loss from inspection failure plus the costs of inspections do not exceed a critical cost value. That is,

$$\max_{s\in[0,N]} L(s)\pi(s,n,N) + c(n) \leqslant L_c. \tag{5}$$

By comparing Eqs. (5) and (2) it is obvious that our model of Sections 2 and 3 is a special case of (5) with $L(s) = L$.

Tables 3 and 4 show results analogous to those shown in Tables 1 and 2, but which are based on infestation-dependent loss as modeled in (5) with $L(s) = sL$; that is, each infested item in a container that gets through the inspection process imposes loss L. The results in Tables 3 and 4 are calculated with the same data as used in Tables 1 and 2; that is, $L = \$10$ million and the inspection cost

Table 3
Robust inspection strategies with infestation-dependent loss

Number of items (N)	2% inspection benchmark	Performance criterion (L_c)									
		0.5×10^6	1.0×10^6	1.5×10^6	2.0×10^6	2.5×10^6	3.0×10^6	3.5×10^6	4.0×10^6	4.5×10^6	5.0×10^6
250	5	21	29	36	41	45	46	50	50	57	64
500	10	21	30	36	40	45	50	53	55	56	61
750	15	21	29	36	41	45	49	53	57	60	63
1000	20	21	30	36	41	46	50	53	58	58	63
1250	25	22	30	36	41	47	51	54	57	62	64
1500	30	22	30	36	42	46	50	55	57	61	64
1750	35	22	30	36	42	47	50	54	57	61	63
2000	40	22	30	36	41	46	51	55	58	61	63
2250	45	22	30	36	42	47	50	54	57	62	64
2500	50	22	30	36	42	46	51	54	59	60	64

Table 4
The minimum number of infested items for which a performance criterion is satisfied and the corresponding minimum percentage of infested items with infestation-dependent loss

Number of items (N)	2% inspection benchmark[a]	Performance criterion (L_c)									
		0.5×10^6	1.0×10^6	1.5×10^6	2.0×10^6	2.5×10^6	3.0×10^6	3.5×10^6	4.0×10^6	4.5×10^6	5.0×10^6
250	182 (72.8%)	84 (33.6%)	56 (22.4%)	43 (17.2%)	35 (14.0%)	30 (12.0%)	26 (10.4%)	23 (9.2%)	21 (8.4%)	19 (7.6%)	17 (6.8%)
500	248 (49.6%)	183 (36.6%)	126 (25.2%)	99 (19.8%)	82 (16.4%)	70 (14.0%)	62 (12.4%)	55 (11.0%)	50 (10.0%)	46 (9.2%)	42 (8.4%)
750	281 (37.5%)	287 (38.3%)	199 (26.5%)	157 (20.9%)	131 (17.5%)	114 (15.2%)	101 (13.5%)	90 (12.0%)	82 (10.9%)	76 (10.1%)	70 (9.3%)
1000	302 (30.2%)	392 (39.2%)	274 (27.4%)	217 (21.7%)	182 (18.2%)	158 (15.8%)	141 (14.1%)	127 (12.7%)	116 (11.6%)	107 (10.7%)	99 (9.9%)
1250	318 (25.4%)	500 (40.0%)	351 (28.1%)	279 (22.3%)	235 (18.8%)	205 (16.4%)	182 (14.6%)	164 (13.1%)	150 (12.0%)	139 (11.1%)	129 (10.3%)
1500	333 (22.2%)	609 (40.6%)	429 (28.6%)	342 (22.8%)	289 (19.3%)	252 (16.8%)	224 (14.9%)	203 (13.5%)	186 (12.4%)	172 (11.5%)	160 (10.7%)
1750	349 (19.9%)	718 (41.0%)	508 (29.0%)	406 (23.2%)	343 (19.6%)	300 (17.1%)	267 (15.3%)	242 (13.8%)	222 (12.7%)	205 (11.7%)	191 (10.9%)
2000	369 (18.5%)	829 (41.5%)	588 (29.4%)	471 (23.6%)	399 (20.0%)	348 (17.4%)	311 (15.6%)	282 (14.1%)	259 (13.0%)	239 (12.0%)	223 (11.2%)
2250	399 (17.7%)	941 (41.8%)	668 (29.7%)	536 (23.8%)	454 (20.2%)	398 (17.7%)	355 (15.8%)	322 (14.3%)	296 (13.2%)	274 (12.2%)	255 (11.3%)
2500	481 (19.2%)	1053 (42.1%)	750 (30.0%)	602 (24.1%)	511 (20.4%)	447 (17.9%)	400 (16.0%)	363 (14.5%)	334 (13.4%)	309 (12.4%)	288 (11.5%)

[a] Evaluated at $L_c = 2.5 \times 10^6$.

function is $c(n) = 1000–2000n + 1000n^2$. Note that by keeping L the same, the potential loss when it depends on the number of infested items that get through the inspection protocol can be substantially higher than in our previous model, which assumed that the potential loss was independent of the number of infested items in a container.

Table 3 presents robust inspection strategies for our example of infestation-dependent loss. In comparison with the data in Table 1, the most obvious difference is that the number of robust inspections is higher with infestation-dependent loss, and substantially so with higher L_c. This difference is due to the fact that our example of infestation-dependent loss involves significantly greater potential loss than our example of infestation-independent loss. Somewhat loosely, maximizing robustness calls for more inspections when the potential loss is greater.

In other ways the data in Table 3 reveal patterns that are similar to those in Table 1. In both there is a general tendency for the number of robust inspections to increase as the performance criterion is relaxed (L_c increases). On the other hand, given a performance criterion, both models suggest that the number of robust inspections does not vary much at all with the number of containers N. Thus, whether the potential loss from inspection failure is infestation dependent or not, inspections increase as the performance criterion is relaxed, but are largely independent of the number of containers in a shipment.

Now turn to Table 4, which contains our robustness measures for infestation-dependent loss. Recall that the whole number in each cell is the minimum number of infested items in a container for which the performance criterion is met, while the second value in each cell is the corresponding minimum percentage of infested items. Comparing the data in Table 4 to Table 2 reveals that robustness in our example of infestation-dependent loss is significantly less than in our example of infestation-independent loss. This is due to two reasons. The first is that the potential loss in our example of infestation-dependent loss is significantly higher. The other is that since more inspections are conducted with infestation-dependent loss, inspection costs are higher. Both of these increase the minimum number of infested items for which a performance criterion is achieved.

Despite this difference, the data in Tables 4 and 2 confirm a general result of models of robust satisficing decisions—decision makers achieve greater immunity if they are willing to tolerate higher expected losses. In our examples, note that the minimum number of infested items as well as the corresponding percentage of infested items both decrease as L_c is increased. Thus, robustness increases as the performance criterion is relaxed.

Finally, as in Table 2, the second column of Table 4 contains the robustness measures of the 2% inspection benchmark, evaluated at the performance criterion $L_c = \$2.5$ million. Again it is clear that the 2% rule can never be more robust, and may be significantly less robust than the optimally robust decisions. This difference illustrates the advantage of following an inspection rule that incorporates economic values associated with inspections and inspection failure, as well as the severe uncertainty surrounding the threat of invasive species introductions.

Perhaps it goes without saying, but one should not take our simulation results, particularly the comparison between the infestation-dependent and -independent cases, as indicative of real-world cases of inspections for invasive species. It is not always true among real-world invasive species that the infestation-dependent loss case would necessarily imply higher loss than the infestation-independent loss case. For example, one case of "mad cow" disease infestation might be sufficient to cause maximum loss in the long run and the loss would not change if infestations were higher to begin with. Alternatively, in case of some other well-known invasive species such as pink hibiscus mealybug and soybean rust, where spatial issues are significant, repeat infestations would have more impact in terms of loss. It is also true that inspection technologies and their costs are likely to vary across invasive species, and may also vary across ports of entry. Thus, it is clear that the determination of robust inspections in particular cases will depend on several factors that we have not modeled. Nevertheless, the robustness approach can easily be modified to account for differences among invasive species problems.

5. Conclusions

Many economic and policy decisions must be made despite decision makers being truly uncertain about elements of the problems they face. This is particularly true in the practice of preventing biological invasions with associated costs to agriculture and consumers and the significant potential for human health impacts in case invaders vector known or yet-to-be discovered zoonotic diseases. Assessing related risks in this arena can be problematic at best. Basing invasive species inspection protocols on economic models of risk is therefore similarly problematic. Moreover, current practice appears to be devoid of economic considerations and does not account for the fundamental uncertainty of the problem. The main contribution of this paper is to point the way toward a new way of dealing with severe uncertainty in the biological inspection realm that incorporates economic data and, as importantly, is free of the problems associated with risk assessment in a truly uncertain environment. The model developed in this paper incorporates economic aspects of inspection and inspection failure via the concept of robustness of choice over severely uncertain model elements. This same approach is applicable to an increasingly wide range of detection problems where uncertainty reigns and effective use of scarce inspection resources are required.

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Integrating drivers influencing the detection of plant pests carried in the international cut flower trade

F.J. Areal[a,*], J. Touza[b], A. MacLeod[a], K. Dehnen-Schmutz[c], C. Perrings[d], M.G. Palmieri[e], N.J. Spence[a]

[a]*Central Science Laboratory, Sand Hutton, York YO41 1LZ, UK*
[b]*Department of Ecological Modelling, Helmholtz Centre for Environmental Research UFZ, 04301 Leipzig, Germany*
[c]*Department of Biology, University of York, York YO105DD, UK*
[d]*ecoSERVICES Group, School of Life Sciences, P.O. Box 874501, Tempe, AZ 85287-4501, USA*
[e]*Centre for the Economics and Management of Aquatic Resources, University of Portsmouth, Portsmouth, Hampshire PO1 2UP, UK*

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Abstract

This paper analyses the cut flower market as an example of an invasion pathway along which species of non-indigenous plant pests can travel to reach new areas. The paper examines the probability of pest detection by assessing information on pest detection and detection effort associated with the import of cut flowers. We test the link between the probability of plant pest arrivals, as a precursor to potential invasion, and volume of traded flowers using count data regression models. The analysis is applied to the UK import of specific genera of cut flowers from Kenya between 1996 and 2004.

There is a link between pest detection and the Genus of cut flower imported. Hence, pest detection efforts should focus on identifying and targeting those imported plants with a high risk of carrying pest species. For most of the plants studied, efforts allocated to inspection have a significant influence on the probability of pest detection. However, by better targeting inspection efforts, it is shown that plant inspection effort could be reduced without increasing the risk of pest entry. Similarly, for most of the plants analysed, an increase in volume traded will not necessarily lead to an increase in the number of pests entering the UK. For some species, such as *Carthamus* and *Veronica*, the volume of flowers traded has a significant and positive impact on the likelihood of pest detection. We conclude that analysis at the rank of plant Genus is important both to understand the effectiveness of plant pest detection efforts and consequently to manage the risk of introduction of non-indigenous species.

Keywords: Alien invasive species; Cut flowers; Plant pest species; Count data models; Phytosanitary inspection

1. Introduction

It has been recognised that the growth and development of world markets has a significant impact on the risk of biological invasions (Perrings et al., 2000; McNeely, 2001). The development of trade routes has opened up new pathways for invasive and potentially invasive species, and increased the frequency of detections and introductions (Frank and McCoy, 1992; Ruiz and Carlton, 2003; Caton et al., 2006; McCullough et al., 2006). This paper examines the invasion risks associated with the development of the international cut flower trade in the United Kingdom (UK), focusing on UK imports of cut flowers from Kenya between 1996 and 2004. Invasion risks are influenced by both environmental and social factors including the invasive species' life cycle strategy,[1] its prevalence on the traded host (which can vary seasonally), its adaptability to new environments, the nature of the trade pathway; and

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*Corresponding author. Current address: Department of Agricultural and Food Economics, The University of Reading, P.O. Box 237, Reading RG6 6AR, UK. Tel.: +44 1189 3785239.

E-mail address: f.j.areal@reading.ac.uk (F.J. Areal).

[1] A pest's life cycle strategy can influence invasion risk, e.g., parthenogenic (asexual) reproduction enables an individual female to give rise to progeny without partner. Thus even if a single individual were introduced, it could potentially generate a pest population.

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the frequency and volume of trade. A more detailed description of the factors contributing to the risk of pest entry is provided in FAO (2004). Since we are concerned with the introductions of species associated with particular pathways (MacLeod and Baker, 2003) and the effectiveness of phytosanitary inspection contributes to likelihood of detection on those pathways (Perrings et al., 2005), we analyse detections not on cut flowers in general, but at the taxonomic rank[2] of plant Genus. More particularly, we analyse (a) the likelihood that pests will be detected as a function of the volume of cut flower imports, by Genus, and (b) the likelihood that an increase in inspection efforts will increase the pest detection rate, again by Genus.

The international cut flower trade has grown in volume and value as a proportion of world trade (AIPH, 2004). This has led to an increased risk of plant pest introductions in importing countries (Kiritani and Yamamura, 2003; Work et al., 2005). Although the problem is not new (Frey (1993) showed that 13% of cuttings and 25% of whole plants imported to Switzerland were carrying arthropod pest species), the increase in the volume of imported plant material has substantially influenced the movement of pests in trade.

At the beginning of the 21st century, the European Union (EU) had established itself as the world's leading importer of cut flowers, accounting for over 50% of the global consumption of cut flowers (CBI, 2002). Not only has the volume of the trade continued to grow rapidly, but so too has the number of countries exporting cut flowers to Europe. African countries are becoming a significant source, currently accounting for around 8% of world exports of cut flowers, at a value of almost US$ 300 million (World Bank, 2005). Kenya was already the largest African exporter with 55% of the African market in 2001 (World Bank, 2005), and continues to dominate the African cut flower trade. It is one of the biggest suppliers of cut flowers to the EU, with 25% market share. Within the EU, the UK is the second largest importer of Kenyan cut flowers, cut flower imports from Kenya into the UK having increased by 239% between 1996 and 2003.[3] The value of cut flowers imported by the UK from Kenya in 2004 was approximately US$82 million.[3]

The Plant Health and Seeds Inspectorate (PHSI) executes plant health policy in England and Wales, part of which is to oversee and enforce import controls by carrying out intelligence-led, targeted, import inspections to inhibit the entry of prohibited plants and plant pests, and to audit those commodities that require a phytosanitary certificate. Upon detection of a regulated pest, there are a number of options available including (a) destruction of the consignment in a prescribed manner, (b) removal of contaminated products within the consignment followed by the release of the remainder of the consignment, (c) quarantining of the consignment pending tests, (d) application of an appropriate pest treatment, e.g., application of chemical insecticides, restriction of the use of the consignment, e.g., fresh produce could be directed for industrial processing or (f) the consignment could be rejected and returned or re-exported.

This paper analyses the effectiveness of inspection regimes in controlling the invasion risks from the increased cut flower trade between Kenya and the UK. In principle, the economics of inspections as a mechanism for controlling invasive species are straightforward. Inspections for pests should optimally be set to the level at which the marginal cost of inspection is equal to the expected marginal damage costs avoided by pest detection, and the various interception and control strategies that inspection supports (Southey, 1979; Ebbels, 2003; Ashby et al., 2005). When the infestation of the imported material reaches a given level in which detection has no effect on damage avoided, there is also a threshold interception rate beyond which it is optimal to not inspect but to charge an import tariff equal to the expected damage of pest imports (McAusland and Costello, 2004). Actual practice however includes import bans or standards. Commodities which, without regulation, present an unacceptable phytosanitary risk, are required to comply with a phytosanitary import standard, e.g., be free from specific plant pests, as noted in the EC Council Directive (2000/29/EC).

Within the threshold described by McAusland and Costello (2004), it follows that if the risk associated with different cut flowers varies (i.e. the level of potential avoided damaged varies), so should the level of inspection effort. In this paper, we test the hypothesis that inspection effort varies with the rate of interceptions. Unlike previous work where cut flowers and cumulative imports were regarded as a single route for pest entry (Levine and D'Antonio, 2003; McCullough et al., 2006) we examined the invasion risks associated with the main imported cut flowers and their individual inspection regimes separately. A count data approach is applied to explore the relationship between the number of pest interceptions, the volume of cut flowers traded and the level of detection effort.

2. Methods

2.1. Data

There are no direct observations on the number of pest species that enter and establish as a result of their presence on imports of different cut flowers (Smith et al., 2005). However, we can obtain a measure of the risk by determining the number of pests intercepted per unit of inspection effort,[4] again by flower type. To test the

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[2] Taxonomists classify organisms using a hierarchy with levels such as Kingdom, Phylum, Order, Family, Genus and species. Each level is referred to as a rank.

[3] *Source*: Based on data prepared by Statistics (Commodities & Food) Division, Defra, provided by HM Revenue and Customs.

[4] In this study, effort is not a measure of time but the number of consignments of each type of cut flower inspected.

relationship between (a) the number of pest species intercepted per cut flower Genus, (b) the number of cut flower consignments inspected and (c) imported volume, we obtained monthly data for the period between January 1996 and March 2004. The dataset consisted of records of plants inspected and plant pests detected by the personnel of the PHSI of the Department for environment food and rural affairs (DEFRA) in the UK. Volumes of cut flowers imported to the UK from Kenya were obtained from the Eurostat Database. The Eurostat Dataset includes data on the volume of cut flowers imported from Kenya to the UK for the following categories: "roses", "carnations" and "other cut flowers". For those plants for which the volume of imports was not available, we used the data on the latter category as a proxy.

Data on pest interceptions do not specify whether the host is a cut flower, a cutting or a plant, while data on inspections distinguish between these types of hosts. Accordingly, in order to make sure that the host of the pest species intercepted was a cut flower, the date of inspection and date when pest was intercepted in both datasets were checked to ensure that they coincided. Only *Dendranthema* was removed from the dataset since it was not possible to say whether the pest intercepted was found in cut flowers or cuttings in every case.

2.2. Count data models

We use count data models to study the variability of monthly pest species interceptions in cut flowers. Count data describe the number of times a given event occurs. Count data models are appropriate when the dependent variable is a variable that takes on nonnegative integer values, $y = 0, 1, 2, \ldots$, where y is measured in natural units on a fixed scale. In our case, this is the number of pest species detected in cut flowers per month. The variable takes discrete values including 0. Count data distributions are characterised by being skewed to the left. Using the count data on interceptions in the study period, we estimated the following models: the Poisson Regression Model (PRM), the Negative Binomial Regression Model (NBRM), the Zero Inflated Poisson (ZIP) and the Zero Inflated Negative Binomial (ZINB). The last three were used to account for the presence of overdispersion and the frequency of zero pest species intercepted.

The number of pest species intercepted was firstly modelled using the Poisson Regression Model, which it is normally the first step for most count data analyses. This approach specifies that the count dependent variable (y) follows a Poisson distribution with expectation parameter λ (i.e. expected number of interceptions per month), $\Pr(Y|\lambda) = (e^{-\lambda}\lambda^{y}/y!)$, $y = 0, 1, 2, \ldots$. One of the main characteristics of the Poisson distribution is that the expectation parameter, λ is both the mean and the variance of the count data (y). This property is known as equidispersion. This Poisson distribution is extended to obtain a regression model by allowing each observation y_i to have a different value of λ. The most popular formulation is an exponential relationship between the expectation rate and a set of regressors, $\lambda_i = e^{x_i\beta}$ where x_i is the vector of regressors that includes the number of phytosanitary inspections and volume imported of cut flowers per month and β is the vector of unknown parameters to be estimated which captures the effect of the number of inspections, and volume of cut flowers imported on the number of interceptions. In practice, the variance of the data is often larger than the mean, i.e. the data are characterised by overdispersion. In this case, the standard errors estimated from the Poisson Regression Model are biased downward and the p-values are small and spurious; therefore, it is important to check for overdispersion (Cameron and Trivedi, 1986, 1990; Dean, 1992). A number of tests have been devised for overdispersion in the Poisson Regression Model. We use a Likelihood ratio (LR) test to determine whether overdispersion is present, i.e. whether the assumption behind the Poisson model, $\text{Var}(y|x) = \alpha E(y|x)$, is satisfied. If overdispersion is found a solution is provided by the Negative Binomial model (i.e. NegBin II), which is usually applied to account for overdispersion. This model allows the variance to exceed the mean. It requires that the variance be equal to $\text{Var}(y_i|x_i) = (1 + \alpha\exp(x_i'\beta))\exp(x_i'\beta)$ for some $\alpha > 0$, where the amount of overdispersion increases with the conditional mean $E(y_i|x_i) = e^{x_i\beta}$ (Cameron and Trivedi, 1986).

Some cut flowers show a large number of zero interceptions. This may occur for two different reasons. It may be that no inspections were conducted or when inspections were conducted no pest was detected. Too high an incidence of zero counts in the data may cause problems if it is greater than expected for the Poisson distribution. Excess zeros or zero inflation in data result in heterogeneity leading to biased coefficient estimates. In addition, the PRM and NBRM do not account for the potential sources of zeros in the dependent variable. In order to account for excess zeros ZIP and ZINB models were estimated (Lambert, 1992). Following Long and Freese (2003) zero inflated models assume that there are two unobserved groups. In one group (G1), the outcome is always zero. In the other group (G2), the Poisson or negative binomial distribution produces the zero outcome or some other. Formally,

$$Y_i \begin{cases} \text{G1}: & 0 \text{ with probability } 1, \\ \text{G2}: & \text{Poisson } (\lambda_i) \text{ or Negative binomial } (\lambda_i, \varphi), \text{ positive outcome with probability } p_i > 0, \end{cases}$$

where Y_i is the count dependent variable and $\varphi \geqslant 0$ is a scalar. When $\varphi = 0$, it reduces the ZINB to a ZIP model.

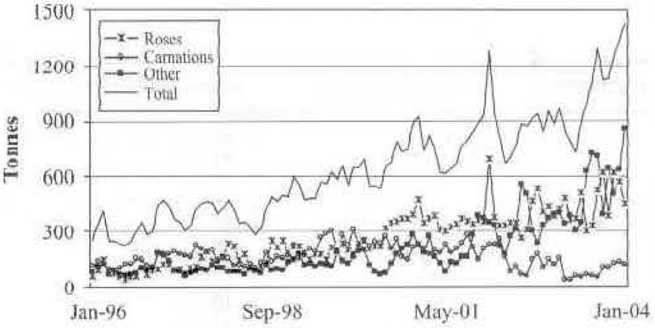

Fig. 1. Imported volume of roses, carnations and other cut flowers between January 1996 and March 2004 to the UK.

We conducted PRM, NBRM, ZIP and ZINB regressions on each individual cut flower to estimate the model parameters. Misspecification of the models was checked using a regression specification error test (RESET). This involved including the squares of the predicted values as an extra covariate in the models (Long and Freese, 2003). Overdispersion was tested by conducting a LR test. This helped to decide between PRM and NBRM. The Vuong's test provides a mechanism for testing hypotheses concerning model validity (Vuong, 1989). Greene (1994, 2003) proposed to use Vuong's test statistic to compare the ZIP model to PRM or the ZIBN to the NBRM. Vuong's test provides evidence of which of the two competing models fits the data best for a given dependent variable (Long and Freese, 2003).

3. Results

The cut flower trade between Kenya and the UK grew rapidly during the study period (Fig. 1), the volume and value (in 2004 US$) of cut flowers imported to the UK having increased by approximately 239% and 326%, respectively, during the period.

A total of 148 pest interceptions, representing approximately 33 species, were reported in 2080 phytosanitary inspections carried out on the set of cut flowers analysed in this study during the 8-year period. Insects were the most common plant pests detected in the inspections (93% of the interceptions) with Diptera (flies) (38%), Thysanoptera (Thrips) (32%) and Hemiptera (21%) as the most frequently detected insects.[5] Data analysis suggests that *Veronica*, *Carthamus*, *Lisianthus* and *Eryngium* are the plants that represent the greatest risk of pest introduction by representing the highest number of pest interceptions per inspection, with on average 30% or more of inspections identifying pest presence (Table 1).

The number of pest species found per interception varied significantly between cut flowers, as did the nature of the pest species associated with each plant type. *Veronica*, for example, yielded pest species in 43% of inspections, 93% of which were Thysanoptera (Thrips), which represents 87% of all the Thrips intercepted (Table 2).

Fig. 2 shows the number of inspections and interceptions of 12 pest hosts throughout the period studied. Significant differences were observed between cut flowers in terms of both the number of inspections and interceptions across the period analysed. The detection effort was distributed unevenly through time for most of the plants considered, with just a few of the flowers regularly inspected. Some flowers such as *Alstroemeria*, *Dianthus*, *Eustoma*, *Gypsophila*, *Limonium*, *Rosa* and *Solidago* were inspected regularly during the period, whereas others such as *Carthamus*, *Eryngium*, *Lisianthus*, *Solidaster* and especially *Veronica* show periods when inspections have not been conducted. It is worth noting that it is an obligation of contracting parties to the International Plant Protection Convention (IPPC) that information is shared about new pest finds and incursions. Protocols for the dissemination of such information, for example through the European and Mediterranean Plant Protection Organisation assists countries to gather intelligence and target inspections. In addition, analysis of past finds informs decision makers on which pathways to target (MacLeod et al., 2005). Local PHSI knowledge and experience also contribute to selecting consignments to inspect.

Table 3 shows the results of the PRM, NBRM, ZIP and ZINB regressions. They show that, in general, the volume of imports and the introduction of pests are not correlated. However, for the particular species *Carthamus* and *Veronica*, import volumes are positively related to the number of pest species intercepted (p-value<0.001). This means that an increase in trade in these cut flowers in particular does increase the risk of pest entry, holding the number of inspections constant. In one case, *Eustoma*, import volumes were found to be negatively related to the number of pest species intercepted. This is due to the fact that the data do not show any interceptions after February 2000 when import volumes of the flower increased. No volume effects were found for the other cut flowers studied.

There is evidence in some cases that the level of inspection efforts was sensitive to the perceived risk. The number of inspections was, for example, found to be positively related to the number of pest species intercepted, holding everything else constant, in the case of *Alstroemeria*, *Carthamus*, *Eryngium*, *Lisianthus*, *Solidago* and *Veronica* (p-value<0.001). This is consistent with recognition that the import of these cut flower genera carries a risk of introducing pest species more than other cut flower genera. However, import volumes and inspections were uncorrelated with the frequency of interceptions in the case of *Rosa* and *Solidaster*. Indeed, the most heavily inspected flowers typically had the lowest interception to inspection ratios (Table 1). The estimates for the expected number of interceptions (i.e. λ)

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[5] Hemiptera are insect bugs. Hemiptera that are plant pests damage plants by feeding on the plant's nutrients and can cause unsightly blemishes to ornamental flowers. Thysanoptera are small winged insects closely related to bugs (Hemiptera) with similar sucking mouthparts and can cause similar plant damage. Diptera are flies. Some juvenile stages (larvae) burrow within a host plant, excavating a mine, weakening the host plant.

Table 1
No. of pest detections and inspections per host

Host	No. of detections	No. of pest species	No. of inspections	Inspections (%)	Interception/inspection (%)
Geranium	1	1	1	0	100.0
Veronica	13	42	30	1.4	43.3
Carthamus	8	10	24	1.2	33.3
Eryngium	9	15	29	1.4	31.0
Lisianthus	20	21	69	3.3	29.0
Hypericum	4	4	25	1.2	16.0
Euphorbia	2	2	14	0.7	14.3
Eustoma	16	17	114	5.5	14.0
Solidago	22	26	184	8.8	12.0
Stachys	1	1	10	0.5	10.0
Gypsophila	13	13	156	7.5	8.3
Solidaster	4	4	64	3.1	6.3
Dianthus	15	17	298	14.3	5.0
Limonium	6	7	121	5.8	5.0
Alstroemeria	7	12	143	6.9	4.9
Bupleurum	2	2	52	2.5	3.8
Aster	2	2	65	3.1	3.1
Rosa	3	3	258	12.4	1.2
Dendranthema			198	9.5	
Other			225	10.8	
Total	148		2080		

Table 2
Number of *Veronica* consignments found to be contaminated with pests

Date	No. of contaminated consignments	Pest types present	No. of species found
June 2001	1	Insect/Hemiptera	1
October 2001	5	Insect/Thysanoptera	9
		Insect/Diptera	1
		Insect/Hemiptera	1
		Fungi/Erysiphales	1
November 2001	3	Insect/Thysanoptera	6
February 2002	2	Insect/Thysanoptera	2
October 2002	2	Insect/Thysanoptera	4
November 2003	2	Insect/Thysanoptera	2
		Insect/Hemiptera	1

are shown in the last column of Table 3. This parameter has been estimated for the average of the total number of inspections and average import volume of cut flowers per month. Results show that cut flowers with the highest expected number of interceptions per month are *Eryngium*, *Carthamus*, *Lisianthus*, *Solidago and Veronica* whereas the cut flowers with the lowest estimates of λ are *Limonium*, *Solidaster*, *Alstroemeria* and *Rosa*.

4. Discussion and conclusions

This study contributes to an understanding of the invasion risks associated with the growth of the international cut flower trade. Using interceptions per inspection as a proxy for the risk of species entering the UK associated with different cut flower imports, we consider both the evidence of invasion risks from the record of inspections and interceptions, and the evidence for the efficiency of the inspection regime. The study shows that the likelihood of pest detection depends mainly on the Genus of cut flowers imported. Recalling that pest inspections should be set to the level where the marginal cost of inspection effort is the same as the expected marginal damage avoided by pest detection (McAusland and Costello, 2004), we find that if the potential economic impacts associated with distinct pests are independent of the specific host facilitating entry of the pest, then detection efforts should be higher for cut flowers with a greater risk of carrying pests known to be of concern, as MacLeod and Baker (1998) demonstrated when examining the threat posed by *Thrips palmi* to EU horticulture.

This analysis has found that the level of inspection effort for most cut flowers is not related to the likelihood of pest detection associated with those flowers.

Our results indicate that for most of the cut flowers analysed, the risk of pest entry did not increase with the volume of imports. That is, for most species, an increase in the volume of imports from Kenya did not lead to an increase in the number of pests intercepted in the UK, holding the number of inspections constant. For *Dianthus*, *Rosa*, *Solidago* and *Solidaster* the growth in import volumes had little discernible effect on entry of pest species. This partly reflects the quality of pest control in Kenya in respect to these genera (D. Grove, PHSI, pers.comm.). However, for *Carthamus* and *Veronica*, this was not the case. For these flowers, the growth in import volumes clearly increased the risk of pest species entering.

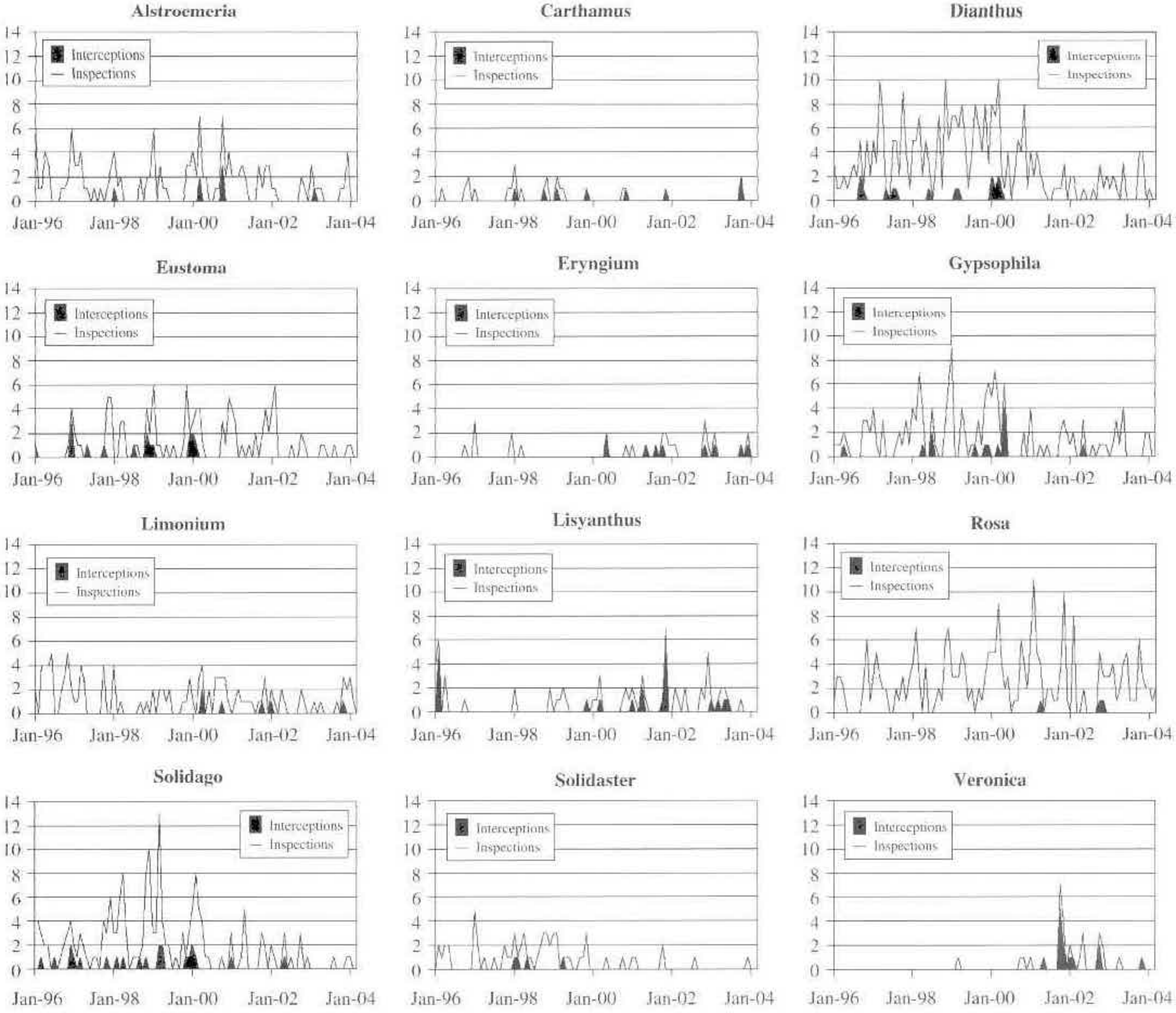

Fig. 2. Number of inspections and interceptions per month of a set of cut flowers between January 1996 and March 2004.

Table 3
Model results

	Constant	Inspections	Log (volume)	Log^{-1}	N	Method	λ
Eryngium	−2.14 (3.33)	2.30** (0.58)	−0.42 (0.63)	−23.97	99	NegBin	1.37
Carthamus	−10.51** (2.30)	1.83** (0.32)	1.25** (0.37)	−16.98	99	Poisson	0.62
Lisianthus	−1.29 (2.32)	0.55** (0.09)	−0.15 (0.44)	−27.55	99	Poisson	0.38
Solidago	1.16 (1.97)	0.24** (0.05)	−0.65 (0.41)	−54.75	99	NegBin	0.19
Veronica	−21.62** (7.10)	0.97** (0.17)	3.52** (1.17)	−18.01	99	ZINB	0.18
Eustoma	6.96 (4.03)	0.57* (0.20)	−2.02*	−38.60	99	NegBin	0.11
Dianthus	2.46 (3.33)	0.24* (0.11)	−1.05 (0.70)	−42.83	99	NegBin	0.10
Gypsophila	4.95 (4.28)	0.47* (0.16)	−1.73 (0.92)	−30.10	99	ZIP	0.05
Limonium	−11.15 (5.71)	1.08* (0.45)	1.18 (0.93)	−19.67	99	Poisson	0.05
Solidaster	10.01 (8.22)	0.57 (0.43)	−2.96 (1.88)	−13.57	99	Poisson	0.02
Alstroemeria	−12.95* (4.89)	1.13** (0.21)	1.22 (0.82)	−14.50	99	Poisson	0.01
Rosa	−22.77* (10.90)	0.09 (0.21)	3.25 (1.81)	−10.57	99	Poisson	0.01

*Significant at 5% level.
**Significant at 0.1% level.

Without detailed data on the expected damage costs of pests or the cost of inspection we are unable to evaluate the optimal level of inspections. However, if we assume that the potential impact of a pest is independent of the species that acts as its host during shipment, we can at least evaluate the efficiency of the relative level of inspection effort for different hosts. We would expect the level of inspection effort for different cut flower hosts to be a function of the level of interceptions (our proxy for the level of expected pest entry associated with those species). We find no such relationship. For *Rosa* and *Solidaster*, we find that the level of inspection effort may be disproportionately high relative to the interception rate. Inspection effort for these species could be reduced without affecting pest entry. For *Alstroemeria*, *Carthamus*, *Eryngium*, *Lisianthus*, *Solidago* and *Veronica*, the level of inspection effort may be below the optimal level. If the potential impact of a pest is not independent of the host, then inspections of each host should increase up to the point where the marginal cost of inspections is equal to the marginal damage avoided by preventing introductions, where the marginal damage cost depends on both the likelihood that a shipment will introduce a pest, and the expected damage if a pest is introduced.

Increasing the level of inspection, and hence interceptions, may reduce the potential impact resulting from pest entry. There is some uncertainty, here, about the threshold interception rate beyond which inspections are no longer helpful. An interception rate above 30% implies a high proportion of infected shipments. If the marginal damage of pest infestation is relatively low in such cases, it can be better not to incur inspection costs, whilst providing exporters with an incentive to reduce the rate of infestation.

When undertaking pest risk analysis (FAO, 2001, 2004), a variety of techniques can be used to estimate pest impacts (Baker and MacLeod, 2005) and when integrated with an economic assessment of the pest management, options can be used to develop or support policy decisions, such as determining an appropriate level of inspection (Surkov et al., 2005). However, normally there is no detailed knowledge on expected damage costs and limited resources are used to inspect high-risk consignments. The European Commission has recently developed a system for better targeting phytosanitary inspections. In determining the minimum level of inspection required, the system takes biotic and abiotic factors into account, such as past pest detections and volume of trade (Anon., 2004). Nevertheless, the new system has been criticised on the basis that it is heuristic, based on value judgements and discriminatory risk classification (Broens and Willems, 2004).

One reason to be concerned about current inspection regimes is that recent regulatory changes may well have increased the likelihood that cut flower imports will be infested, and therefore that the expected marginal damage associated with invasions may be increasing. Since EU regulations on pesticide use were changed in 2000 many pesticides have been withdrawn from use. EU importers often require export partners to follow domestic EU legislation with respect to pesticide use (Chan and King, 2000). Thus, the withdrawal of dichlorvos, an insecticide previously commonly used on cut flowers, may increase pest problems at Kenyan sites.

Further research following the principles of pest risk analysis, using pest interception data on novel trade routes that includes cost data on both inspection effort and the value of potential pest damage could help identify an optimal inspection regime for specific trade routes and imported commodities. It could also be used to detect emerging trends in risk and provides an evidence base upon which management and legislative changes can be assessed (MacLeod and Baker, 1998; Touza et al., 2007; Knowler and Barbier, 2005). Subsequent analysis of pest interceptions that compares interceptions before and after legislative changes can provide a measure of how effective the legislative changes have been (MacLeod et al., 2005).

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NAFTA and member country strategies for maritime trade and marine invasive species

Linda Fernandez*

Department of Environmental Sciences, University of California, Riverside, CA 92521, USA

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Abstract

Maritime shipping has two vectors of spreading marine invasive species: ballast water inside the ship and biofouling on the hulls outside the ship. While some attention has focused on ballast water, virtually none is focused on biofouling. This paper offers a quantitative analysis of economic incentives for shippers and regulating ports to address both pollution vectors. The strategies to address the vectors are induced by incentive mechanisms involving liability, subsidies and taxes. Results show these offer ample incentives in order to truly foster abatement of both vectors. Data from North America's Pacific coast is included in the analysis.

Keywords: Marine invasive species; Ballast water; Hullfouling; Pollution control policies; Economic incentives

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1. Introduction

Ships transporting goods, people and services between different places represent a vector for spreading invasive species throughout the world's oceans (Hayes and Sliwa, 2003). Ships are mobile aquaria as species ranging from pathogens to fish hitchhike in ships' ballast water and attached to a ship's hulls as biofouling (Fofonoff et al., 2003). The main impacts of invasive species are negative impacts on human health and decreases in economic production activities based on marine environments and resources such as fisheries, aquaculture, tourism and marine infrastructure (Pimental et al., 2005).

Approximately 50% of shipping traffic to California takes place within 200 miles of the coastal mainland, primarily from vessel traffic between Mexico and Canada, two of California's largest trading partners through the North American Free Trade Agreement (NAFTA) (GAO, 2002). These vessels are neither subject to any regulations for ballast water nor biofouling. Time and fuel considerations by shippers on the north–south route have not prevented the introduction of these species. For example, Levings et al. (2004) shows that ships traveling north from California and Mexico transport large numbers of invasive species into British Columbia, Canada. Therefore, current US and Canadian policy to prevent the spread of marine invasive species in the Pacific coast of North America is inadequate.

New policies are needed to promote biosafety and address invasive species along coastlines on a multinational scale. In 2004 the International Maritime Organization (IMO) formulated a numerical limit guideline for ballast water emissions (IMO, 2004). Biofouling emissions did not receive the same attention. Ultimately, the control effort will depend on the actions taken by shippers that in turn depend on economic incentives. The paper seeks to analyze the potential for reducing the threat of invasive species under a few policy options.

There is a paucity of economic analysis of invasive species, and virtually none on aquatic invasive species, nor policies to regulate the biological pollution problem. Thus far, economic studies by Perrings (2002), Costello and McAusland (2003), and Olson and Roy (2002) of invasive species have focused on theoretical models of agricultural commodities that might harbor insects. These studies

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*Tel.: +1 951 827 2955; fax: +1 951 827 3993.
E-mail address: linda.fernandez@ucr.edu

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address intentional vectors of introduction for invasive species with a focus on establishing a hazard rate for eradication assuming arrival of an invasive species with the traded agricultural good. Transportation separate from the traded goods as a mode of unintentional species invasion has not been addressed in the economic literature.

Biologists assert prevention is necessary to abate invasive species due to risk and uncertainty of locating exact emissions per ship from both vectors (ballast water and biofouling) uniformly across time and space and ineffective eradication (Ruiz and Carlton, 2003). Preventative policy measures exist but there has not been an economic analysis of their general cost effectiveness and the incentives for shippers and ports. The paper will focus on the various incentives for publicly managed ports and private sector ship operators to prevent and control invasive species.

Because of the difficulty of attributing damage ex post to a shipper through liability involving legal proceedings, Segerson (1995) suggests combining liability with an ex ante instrument. For invasive species, an ex ante instrument is relevant in order to foster needed prevention and formally internalize the externalities. The IMO has regulations related to the prevention, operation and maintenance for flagged states and ships (Llacer, 2004). The statutorily imposed liability for general marine pollution through flagging and registering a ship for ocean transportation is the context for a more focused policy on invasive species. The ship can be held liable regardless of the amount of care exercised. The form of joint and several liability where the court can apportion one party responsible for full damages regardless of relative contribution would make this parallel to strict liability for shippers. In principle, the anticipation of the liability can be incentive enough to reduce risk of damage. However, this incentive may be less effective if polluters face limited financial liability and avoid paying damages by becoming insolvent (Sterner, 2003).

This paper addresses risk of damages and asymmetric information between the regulator and shipper in the context of two emissions vectors (ballast water and biofouling) that require more than one policy to address them. The optimal regulatory policy depends on information provided by the shipper since they know more about what abatement happens on the ship than the regulator. The difficulty of attributing damage ex post to a shipper under liability motivates the study of the efficacy of ex ante measures.

The choice of optimal regulatory policies with two vectors (ballast water and biofouling) of emissions is examined under conditions of (1) risk surrounding the potential magnitude of the damages and (2) asymmetric information between the regulating port and the shipper regarding the shipper's potential liability for any damage costs. A combination of two policies is used to address the market failures. The combination consists of liability and subsidies as well as liability and taxes.

The analysis of these policies is contrasted with an initial Case 1 that does not formally recognize both sources of emissions and possible damages. Case 2, where both sources of emissions and damages are fully accounted for, approaches reality and enables the variety of policies to be assessed for the potential to help address marine invasive species pollution. The modeling approach considers incentives for both the regulating port and the shipper facing any regulation and evaluates the optimality of possible policies for both key entities. Specifically, Case 2 contains the following components: (1) the International Maritime Organization (IMO) emissions standard; (2) both the shipper and regulating port realize the potential for biofouling damage that has a risk distribution; (3) strict legal liability of the shipper for any damages; (4) a per cubic meter subsidy; (5) a fixed fee to pay for an emissions monitoring program and any necessary damage abatement costs, where the fee depends on a ship-reported estimate of the potential severity of damages, should they occur. Assuming there is asymmetric information on the potential severity of damage, should it occur, the shipper has more information than the regulator on potential the severity due to knowledge of the abatement.

Results show incentive-based policies (subsidy with liability rule or tax with liability rule) help avoid marine invasive species pollution when there are uncertain damages and asymmetric information between shippers and the regulating port. When liability is high, shipper profits are higher and social welfare is lower under regulation. Liability does not affect abatement choices, only the distribution of rents. Subsidies and taxes achieve the same level of abatement and welfare. While shipper profits are slightly lower with profits, damages are significantly lower.

2. Model

The model takes the IMO standard on ballast water emissions to the ocean as a given policy and seeks to determine how best to regulate impacts from more than ballast water emissions in order to also address biofouling emissions. The analysis reflects the second best, fragmented nature of current environmental regulation. The shipper is assumed to know the standard. The environmental goal of the IMO standard is a numerical goal of risk reduction in a safety-first manner, focused on ballast water emissions.

The regulating port minimizes total social costs of shipping including any potential environmental costs subject to meeting the IMO standard. The shipper maximizes expected profits. Assume that shipping has constant returns technology, so any changes in shipping costs translate to changes in production costs per cubic meter of emissions.

Two cases are modeled. In the first model, biofouling emissions are imposed on the IMO ballast water standard. Then, the shipper chooses the amount of ballast water emissions to release to the ocean to meet the IMO standard at least cost. Without biofouling damages formally accounted for in setting the standard, the shipper's choice matches the regulator's socially-optimal (second-best, given the level of the IMO standard) selection.

The second model considers a regulatory framework that may help regulating ports avoid some of the "unintended consequences" of uncontrolled invasive species. This model allows for (1) the possibility of both ballast water emissions and biofouling emissions with damages in formulating the regulations and (2) asymmetry regarding estimates of the shipper's potential liability for any invasive species impacts. Thus, this model provides a realistic description of most pollution regulation decisions. The regulatory instruments to be tested in this model include liability, subsidies and taxes. The subsequent sections derive sequentially the optimal emissions and policy levels. It will be shown that liability combined with subsidies has similar results as liability in combination with taxes. Functional forms are based on the empirical setting with properties for computational ease.

2.1. Case 1 with IMO emission standard regulation

The shipper maximizes profits by selecting a combination of ballast water emissions B_1 and biofouling emissions B_2 for ocean release to meet the IMO standard. Table 1 lists model symbols. Eq. (2) indicates the IMO standard for ballast water augmented by adding biofouling emissions, another vector of invasive species released by ships to the ocean.

The model is developed on a "per cubic meter of emissions" basis to indicate a volume measure for aqueous emissions commonly used in the maritime shipping context, containing an amount (percentage) of invasive species. Eq. (1) indicates that the shipper maximizes profit per cubic meter of emissions, π, by choosing to release to the ocean some amount of ballast water emissions B_1 in the tank and volume of biofouling emissions B_2 attached to the ship hull. Prior to release to the ocean, ballast water treatment onboard serves to filter and remove invasive species in the ship's emissions. Since marine invasive species can be sessile as well as suspended in aqueous emissions, biofouling consists of the volume of invaders attached to the ship as it moves from one port to another with wet weight, not dry weight. It is necessary to also measure this vector of emissions in cubic meters from which sessile invaders can be filtered and removed. Prevention to address both emissions will be discussed later.

Table 1
Model notation

π = shipper net profits per cubic meter
r = shipper profits per cubic meter of emissions
B_1 = cubic meters of ballast water emissions
B_2 = cubic meters of biofouling emissions
c_1 = cost per cubic meter of ballast water emissions
c_2 = per cubic meter of biofouling emissions
$\bar{I}$ = IMO emissions standard constraint in percent of invasive species
a_1 = percent per cubic meter content of invasive species in ballast water emissions B_1
a_2 = percent per cubic meter content of invasive species in biofouling emissions B_2
s = subsidy per cubic meter
S = lump-sum subsidy
α_i = shipper's true liability share
α_i = shipper's reported liability share
D = invasive species damage index
$p(D)$ = probability density function of random variable D
λ = location parameter of exponential probability density function
$M_1 = c_2(a_1/a_2)\text{-}c_1$, derived parameter
$M_2 = 2D(\bar{I}/a_2)(a_1/a_2)$, derived parameter
$M_3 = D(a_1/a_2)^2$, derived parameter
$M_4 = c_1a_2/a_1 - c_2$, derived parameter
t = fee per cubic meter
F = lump-sum fee

Eq. (2) describes the IMO constraint on invasive species released to the ocean from ship emissions. Eq. (2) describes the fixed-proportions relationship that exists between the emissions vectors and the standard $\bar{I}$. The IMO sstandard, $\bar{I}$, is set at a numerical limit of 0.02 that is based on a percentage of invasive species (allows for various species and sizes) (Ambroggi, 2004). While the IMO has focused on B_1, it is useful to include B_2. There are fixed dimensions of ballast water tank size and surface area for ships to follow the form of Eq. (2). For example, typically 30% of a ship's weight is the quantity of ballast water capacity for that ship (Langevin, 2003). The shipper's profit maximization problem is

$$\max_{B_1,B_2} \pi = r(B_1 + B_2) - c_1B_1 - c_2B_2 \tag{1}$$

$$\text{s.t.}: \ a_1B_1 + a_2B_2 \leqslant \bar{I}. \tag{2}$$

Non-negativity constraints on B_1 and B_2 are: $B_1 \geqslant 0$ and $B_2 \geqslant 0$. Parameter r in Eq. (1) is the shipper's transportation profit margin per cubic meter of emissions. In this manner the shipper's earnings can be tied to the transportation activity he performs separately from the trade revenue. This distinction helps to investigate the transportation realm where r is the monetary value multiplied by the amount of invasive species emissions released to the ocean from the tonnage transported. The amount of shipping can be gauged by r and the following production relationship links emissions to shipping, $r = F(V)$. The technology $F(V)$ indicates the amount of invasive species emissions produced (and released) when the current shipping of the port is r in a manner that has been modeled in the environmental economics literature by Forster (1973). In this case, V is made up of both B_1 and B_2, according to $V = B_1 + B_2$.

The shipper's profit margin, r, is approximately $0.27 per cubic meter of emissions carried by the ship (Helling and Poister, 2000).

Parameters a_1 and a_2 in Eq. (2) represent the percentage of invasive species per cubic meter of biofouling and the percentage of invasive species per cubic meter of ballast water emissions, respectively. Fofonoff et al. (2003) indicate reference values for both a_1 and a_2 based on time series data of the percentage of invasive species per cubic meter of ballast water and hullfouling emissions. Parameter a_1 is 0.35% per cubic meter of ballast water emissions, based on the typical dry weight of invasive species in the liquid volume of ballast water emissions (Ruiz and Carlton, 2003). Parameter a_2 is 0.18% per cubic meter of biofouling emissions.

The cost parameters c_1 and c_2 in Eq. (1) are the costs to filter, remove and release the invasive species per cubic meter of ballast water emissions (c_1) and biofouling emissions (c_2), respectively. Shipper's costs for biofouling emissions are 9–13 cents per cubic meter based on a range of six technology options for anti-fouling coatings that have different enzyme and phytochemical bases (Johnson and Miller, 2002). Fouling growth creates enough friction, or "drag" to slow boats and increase fuel consumption, in some cases by 30% (Younqlood et al., 2003). The cost of biofouling due to reduced fuel economy is 4 cents per cubic meter due to up to 10% drag that translates into a 1% loss of fuel from biofouling emissions (Milne, 1990). This amount is then subtracted from the biofouling cost as a gain to fuel economy by the ship. Hence, c_2, is set at the midpoint of the cost range, 7 cents per cubic meter of biofouling emissions.[1] The sealants are variable costs in terms of the rate of application and maintenance, to release biofouling emissions off the hulls. In the event of fixed costs, they can be adjusted to annual figures using a discount rate of 5% for an equipment lifetime of 10 years. The 10 years lifetime is determined by the assessment of duration of effectiveness by Johnson and Miller (2002). The fixed costs are proportional to cubic meters of emissions since they are based on flow capacity. Then, it is possible to sum variable and fixed costs in the per cubic meter estimate of costs.

The cost of ballast water emissions, c_1, is approximately $2.38 per cubic meter of emissions, the midpoint of a range of a couple of technology choices, that imply emissions are gleaned thereby lowering the concentration of invasive species. Since ballast water exchange is not reliable it is important to include the costs of alternative technology that includes physical and chemical processes of deoxygenation and ultra violet treatment (Taylor et al., 2002; Tamburri et al., 2002). In this case, the variable and fixed costs are calculated on a per cubic meter basis for the cost range stated above that are applied to glean the volume of ballast water emissions, where the fixed costs are adjusted through discounting over the equipment lifetime to combine with variable costs by applying a 5% discount rate and an equipment lifetime of 20 years. The lifetime is referenced from Taylor et al. (2002). These fixed costs are proportional to cubic meters of emissions.

The linear constraint in Eq. (2) that adds both types of emissions (sessile organisms from the ship hull and suspended organisms in ballast water) arriving at the port facing the IMO standard is aligned with trend evidence from Fofonoff et al. (2003) and implies a corner solution where one of the two decision variables is positive as determined by the relative values of the parameters c_1, c_2, a_1 and a_2. When $r-a_1/c_1<r-a_2/c_2$ (as is the case for ballast water emissions and biofouling emissions), the solution to the linear programming problem (1)–(2) is given by:

$$B_1^0 = 0, \quad B_2^0 = \frac{\bar{I}}{a_2}. \tag{3}$$

The firm chooses to use $B_2^0 = 0.11$ cubic meters of biofouling emissions (and zero percent of ballast water) to meet the IMO standard $\bar{I}$, given that there is incentive to cut down on drag weight from growth on the ship hull that demands additional fuel. Eventually, fouling growth leads to damage to hull and vessel deterioration (Rolland and DeSimone, 2002). These effects would be another incentive on the part of shippers to implement some action to prevent fouling as a vector of marine invasive species. Without emissions from both vectors, both the firm and the regulating port focus on biofouling emissions to meet the IMO standard, at least cost.

2.2. Case 2 with regulation accounting for dual vectors of biofouling and ballast water emissions

This case considers the shipper's ex ante decision on emissions and the regulating port's ex ante decision for regulating the *potential* for dual vectors of emissions (biofouling and ballast water). The IMO standard in Eq. (2) was set based only on damages from ballast water emissions (IMO, 2004). Therefore, the following model includes quadratic damage costs from biofouling emissions explicitly in addition to damages from ballast water emissions accounted for in the IMO standard. The damage costs of biofouling do not overlap with the content of Eq. (2) where the standard is set based on ballast water emissions only. The biofouling added in Eq. (2) indicates the typical dry weight amount if one attempts to divide between two sources of invasive species: ballast water and biofouling.

The regulating port defines expected social welfare $E(W)$ as expected shipper profits less invasive species damages. The explicit specification here of biofouling damages compensates for the fact that Eq. (2) was not set with consideration for biofouling damages, only those of ballast water. So, the previous section was an attempt to augment the standard by including biofouling. However, biofouling damages had not been formally measured in that case. Ex post estimates of the invasive species damages are measured per cubic meter of biofouling emissions and are quadratic in B_2, that is, invasive species damages per cubic meter of biofouling emissions as $D\ (B_2)^2$ with an exponential probability distribution. An index of invasive

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[1] Parameter values indicate the estimate of biofouling emissions per cubic meter is an average of the range of biofouling treatment costs reduced by the fuel economy savings.

species damage, D, indicates damage to native shellfisheries which have commercial and recreational value. Ex post estimates of average invasive species damage costs range from \$0.06 to \$0.16 per cubic meter of biofouling emissions, including cleanup costs for the Pacific coast of North America (Department of Fisheries and Oceans Canada, 2002; Estado de Baja, 2003; Zentner et al., 2003). The upper limit of this range is considered a lower bound of actual damage costs due to limited data that do not cover the entire Pacific coast of the three NAFTA countries. Estimates from Alaska Department of Fish and Game (2002), Department of Fisheries and Oceans Canada (2002), EDAW, Inc. (2003), Estado de Baja (2003), Hanemann (2003) are for locations along the Pacific coast from the same time period that could be associated with a per cubic meter biofouling emissions in terms of impacts on production quantity and values of shellfisheries (market and non-market values are averaged for the damage measure). These estimates provide the factor income valuation approach where the per cubic meter marginal unit of biofouling emissions displaces a quantity of native shellfish that have the commercial and recreational value indicated in the estimates obtained for the damages.

The mid-point of the range of ex post damage cost estimates is \$0.11 per cubic meter of biofouling emissions. This midpoint serves as the regulating port's ex ante estimate of mean damage costs per cubic meter of biofouling emissions. Mean damage cost corresponds to the actual amount of biofouling emissions, $B_2^0 = \bar{I}/a_2 = 0.11$, and enables solving for the mean value of the damage severity index, denoted $\bar{D}$, as: $\$1.00 = \bar{D} \cdot (B_2^0)^2 = \bar{D} \cdot (0.11)^2 \Rightarrow \bar{D} = 82.64$. The 0.11 is damage per unit of aqueous biofouling emissions, while the \$1.00 is per unit dry weight of invasive species in aqueous biofouling emissions.

The ex post value of D is a random variable, ex ante, from the perspective of both the port and the shipper. Suppose it is common knowledge, ex ante, that D follows an exponential probability density function with location parameter λ, (i.e., $p(D) = \lambda e^{-\lambda D}$) because this form has qualitative properties such as the shape that enables modeling unexpected events. For the exponential density function, $\bar{D} = 1/\lambda$; hence, $\lambda = 1/\bar{D} = 0.0121$, based on initial estimates of the biofouling emission damages to native shellfisheries, commercial and recreational values (in US dollars) in Mexico, US and Canada. The probability density function from the exponential distribution and quadratic damages indicates that the ex ante probability of small multiple externality damages is high, and the ex ante probability of large multiple vector damages is low. The biological basis is from Williamson and Fritter (1996) who developed a statistical or probability based approach for characterizing the outcomes of an invasion known as the tens rule where, over various steps of a possible biological invasion, each step has a one in ten probability of leading to ultimate invasion (from initial dispersal, arrival, spread, establishment, damage). This rule is thought to be applicable to marine invasive species by several marine scientists (Ruiz and Carlton, 2003; Orr, 2003).

With this specification of potential multiple vector damage costs, the port chooses ballast water emissions, B_1, and biofouling emissions, B_2, to maximize expected welfare subject to the IMO constraint. The regulating port's problem is

$$\begin{aligned} \max_{B_1,B_2} E(W) = \int_0^\infty & [r(B_1 + B_2) - c_1B_1 \\ & - c_2B_2 - DB_2^2] \cdot \left(\lambda e^{-\lambda t}\right) \mathrm{d}t \end{aligned}$$
$$\text{s.t.} \quad a_1B_1 + a_2B_2 \leqslant \bar{I} \text{ (IMO constraint)}. \tag{4}$$

Solving the constraint for B_2 from Eq. (3) and substituting into the objective function

$$\begin{aligned} \max_{B_1} E(W) = \int_0^\infty & \Bigg[r(B_1 + B_2) - c_1B_1 \\ & - c_2\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right) \\ & - D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right)^2\Bigg] \\ & \times \left(\lambda e^{-\lambda t}\right) \mathrm{d}t, \end{aligned} \tag{5}$$

the first-order condition for the problem is

$$\begin{aligned} \frac{\partial E(W)}{\partial B_1} = \int_0^\infty & \left[r - c_1 + c_2\frac{a_1}{a_2} + 2D\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) \right. \\ & \left. - 2D\left(\frac{a_1}{a_2}\right)^2 B_1\right] \cdot \left(\lambda e^{-\lambda t}\right) \mathrm{d}t \equiv 0. \end{aligned}$$

or, defining $M_1 \equiv r + c_2(a_1/a_2) - c_1$, and distributing the integral across the terms of the integrand:

$$\begin{aligned} \frac{\partial E(W)}{\partial B_1} = M_1 \cdot \int_0^\infty \left(\lambda e^{-\lambda t}\right) \mathrm{d}t + & \left[2\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) \right. \\ & \left. - 2\left(\frac{a_1}{a_2}\right)^2 B_1\right] \cdot \int_0^\infty D \cdot \left(\lambda e^{-\lambda t}\right) \mathrm{d}t \equiv 0. \end{aligned}$$

Evaluating the left-hand integral above via the method of u-substitution (with $u = -\lambda t$), and the right-hand integral via the method of integration by parts (with $u = D$ and $v = -e^{-\lambda t}$), leaves:

$$\begin{aligned} \frac{\partial E(W)}{\partial B_1} = M_1 + & \left[2\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) \right. \\ & \left. - 2\left(\frac{a_1}{a_2}\right)^2 B_1\right]\left(\frac{1}{\lambda}\right) \equiv 0. \end{aligned} \tag{6}$$

Solving (6) for the port's optimal value of B_1

$$B_1^* = \frac{M_1 + 2\bar{I}/a_2(a_1/a_2)(1/\lambda)}{2(a_1/a_2)^2(1/\lambda)}. \tag{7}$$

Eqs. (7) and (8) take into account damages, costs and relative contributions of ballast water emissions and biofouling emissions into the adjusted IMO limit, instead of one emissions vector.

The port's optimal value of B_2 is obtained via the IMO pollution regulation constraint:

$$B_2^* = (\bar{I}/a_2) - (a_1/a_2)B_1^*. \tag{8}$$

2.2.1. The role of liability

The form of shipper's liability is joint and several liability arising from shipping registration. Shippers are parties to the share of costs that lies between zero and one (a percentage), and the shipper's expectation is that the share is α. This share can be viewed as the probability of damage detected being attributed to the shipper to assume liability. Without ex ante regulation, the shipper chooses B_1 and B_2 to maximize expected profit (including any multiple vector damages for which the shipper is liable), $E(\pi)$, subject to the IMO regulation constraint and its anticipated share of any multiple externality damages. Given the parameters, the shipper bears damage costs αDB_2^2, contingent on the probability of pollution, and this is subtracted from the previous profit maximization. The revised profit maximization is shown in Appendix.

As the shipper's anticipated liability share α decreases, the new abatement value of $\hat{B}_1$ decreases and $\hat{B}_2$ increases, deviating from the socially optimal values for treatment of B_1^* and B_2^* derived previously. Thus, strict liability encourages precaution when there is a risk of damages. Joint and several liability may result in less than optimal control of both biofouling and ballast water emissions. Preventative action with liability could take place within the existing framework of ship registration. The registration involves certifying security measures that include addressing marine pollution. The International Ship and Port Facility Security Code that ships must abide by after July 1, 2004 (IMO, 2002), could emphasize that ships maintain pollution control in order to be able to engage in shipping activity.

2.2.2. Use of a subsidy incentive policy

The regulator uses a subsidy[2], s, per unit of B_1 to ensure that the firm's chosen levels of B_1 and B_2 are consistent with the planner's optimal levels B_1^* and B_2^*. The subsidy is viable through an existing program such as the Experimental Ballast Water Treatment Systems STEP Program run by the US Coast Guard for allocating funds to offset costs of alternative gleaning technology (United States Coast Guard, 2004). The socially optimal subsidy depends on the shipper's anticipated liability share for invasive species damages α. Since the instrument is on a per cubic meter unit basis, it enables flexibility for the shipper to choose amongst technology alternatives depending on vessel characteristics (surface area and ballast water capacity). In this manner, the instruments allow for heterogeneity of ships and can be considered more efficient than a uniform instrument. There is asymmetric information between the shipper and the regulating port regarding α. The shipper's *true* anticipated liability share α_t is known only to the shipper from filtering and removal efforts. The shipper may choose to *report* a liability share α_r different from the *true* share α_t in an attempt to manipulate the regulating port and increase expected shipper profits. This is a plausible feature of the model since the existing *W.* Coast Ballast Water Reporting Program simply collects information that shippers report to ports. No verification is made. In addition to the per unit subsidy s, the regulating port pays the firm a lump-sum subsidy[3] S (derived in Appendix) to ensure that the shipper reports its true anticipated liability share.

The difference between these values and those in Eq. (10) is that the subsidy in the numerator of B_l will mean more emissions are filtered and removed before release since the marginal savings to the shipper from the amount of ballast water emissions and biofouling emissions is equal to the contribution to the emissions target, taking into account the subsidy.

The port determines the per-unit ballast water subsidy rule $s(\alpha_r)$ necessary to ensure optimal abatement B_1^* under the assumption that the lump-sum subsidy $S(\alpha_r)$ will ensure that the shipper will report its true liability share, that is, under the assumption that $\alpha_r = \alpha_t$ (this assumption is verified in Appendix A). The ideal regulation is one with incentive (expected profit) for the shipper to reveal the truth.

The per unit subsidy offered for the shipper to abate works assumes the shipper knows that this is used to determine the lump-sum subsidy. It is plausible since the lump-sum subsidy programs of the US Coast Guard are announced to shippers based on some form of cost sharing. This lump-sum does not require additional terms such as the probability of auditing if the subsidy were based on verifying that the shipper had implemented the optimal B_1 and B_2.

2.2.3. Use of a tax incentive policy

In this section, although optimality conditions may be the same as under optimal subsidies, the number of shippers will be lower in the long run under taxes as profits will be lower (Baumol and Oates, 1988).

The port uses a per unit tax, t, assessed per unit of B_2, to ensure that the shipper's chosen levels of B_1 and B_2 are consistent with socially ptimal levels B_1^*, B_2^*. As shown in Appendix, the socially optimal tax depends on the

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[2] Ballast water reporting and offloading fees for ships according to the California State Lands Commission are lower than actual costs, thereby representing a subsidy.

[3] Since the model is parameterized on a cubic meter basis, this subsidy is drawn from the current ballast water reporting fee uniformly charged per boat to cover some administration costs (California State Lands Commission, 2003). This fee can be adjusted based on the potential severity of invasive species costs. For example, the current fee of $0.012 per cubic meter of untreated ballast water is not sufficient to cover cleanup costs or reporting costs for all boats, and it could be raised to $0.048-$0.21. The lump-sum subsidy S can be envisioned as a *reduction* in the ballast water fee.

shipper's anticipated liability share for multiple vector damages α. There is asymmetric information between the shipper and the port regarding α. Only the shipper knows the *true* liability share α_t. In addition to the per unit tax t, the port imposes a lump-sum fee F (derived in Appendix) on the shipper to ensure that the shipper reports the true liability share. Both the per unit tax t and the optimal lump-sum fee are functions of α, that is, $t(\alpha)$ and $F(\alpha)$. The shipper may choose to *report* a liability share α_r different from the *true* share α_t in an attempt to manipulate the port's choice of t and F and increase shipper profit. The shipper's problem under tax regulation is to maximize expected profit $E(\pi)$, including any invasive species damage liability, per-unit ballast water tax t, and lump-sum fee F, by choosing B_1 and B_2 subject to the IMO constraint.

The level of both types of emissions is based on the marginal benefit to the firm equal to the marginal expected tax, taking into account liability and the contributions of these emissions to the IMO standard as shown in Appendix.

The shipper's profit-maximizing choice of α_r under tax regulation in Appendix shows that the incentive mechanism, the lump-sum fee F offered by the port to the shipper will ensure that the shipper's reported α_r equals the true α_t.

With parallel logic from the derivation of the subsidy, the following relates to investigation of the optimization components that depend on liability. Under the assumption that the lump-sum fee F ensures that $\alpha_r = \alpha_t$, the regulated shipper's expected profit $E(\pi(\ddot{B}_2(\alpha_t)))$ varies with the *true* liability share α_t.

Table 3
Solution values for the multiple externality model, with subsidy incentive mechanisms

Panel a—subsidy values, s^*, S^*

α_r	0.5	0.75	0.99
s^*	1.121944	0.560972	0.022430
S^*	0.060001	0.090001	0.118802

Panel b—ballast water, $\bar{B}_1$

α_r	0.5	0.75	0.99
α_t			
0.5	0.53479	0.51648	0.49889
0.75	0.54701	0.53479	0.52307
0.99	0.55293	0.54367	0.53479

Panel c—biofouling, $\bar{B}_2$

0.5	0.07123	0.10685	0.14104
0.75	0.04749	0.07123	0.09403
0.99	0.03598	0.05397	0.07123

Panel d—Shipper's expected profit, $E(\pi)$, per cubic meter

0.5	0.268167	0.268167	0.268167
0.75	0.267140	0.267140	0.267140
0.99	0.266153	0.266153	0.266153

Panel e—Expected social welfare, $E(W)$, per cubic meter

0.5	0.146110	0.145083	0.142163
0.75	0.145654	0.146110	0.145689
0.99	0.145103	0.145869	0.146110

3. Numerical results for the multiple ship externality model

Table 2 indicates the parameter values used in the derivation of numerical results in subsequent tables. Table 3 results are presented in four panels. Panel a gives the regulating port's choice of per-unit ballast water subsidy s and lump-sum subsidy S based on the shipper's reported multiple vector damage liability share α_r. Notice that the subsidies vary inversely with respect to one another as the shipper reports larger values of α_r. If the shipper reports a small value of α_r, that is, if the shipper reports that its liability share for multiple vector damages will likely be small, then a large per-unit ballast water subsidy, s, is chosen by the regulating port, because an unregulated shipper would otherwise largely discount multiple vector damages and select an inefficiently low level of ballast water control and an inefficiently high level of biofouling control. As the shipper's reported value of α_r increases, the shipper's increasing liability for multiple vector damages serves as an increasingly sufficient incentive for the firm to select the socially optimal combination of ballast water emissions and biofouling emission. As a result, the per-unit ballast water subsidy necessary to ensure that the firm selects the socially optimal combination decreases.

Table 2
Parameter values

Parameter	Value
r	0.65
c_1	\$2.38
c_2	\$0.07
a_1	0.35
a_2	0.18
$\bar{I}$	0.01
B_2^0	0.11
λ	0.0121

If the regulator relied on the ballast water subsidy alone as the sole policy instrument, the firm would have an incentive to report small values of α regardless of the true liability share in order to manipulate the regulating port into providing large ballast water subsidies. The regulating port uses the lump-sum subsidy S to combat the shipper's incentive to report false values of α. If the shipper's reported value α_r is small, the shipper receives a large lump-sum subsidy. The size of the lump-sum subsidy decreases as the shipper reports larger values of α. As shown in the model description, the regulating port's rules for selecting values of s and S that vary inversely with one another ensure that the shipper cannot increase its profits by reporting a false value of α.

Panels b and c of Table 3 illustrate how the shipper's ballast water emissions B_1 and biofouling emissions B_2 vary with the shipper's true invasive species damage liability share α_t and the shipper's reported liability share α_r. As the shipper's true vector liability share α_t increases, the shipper gleans more ballast water emissions B_1, which helps reduce pollution, and gleans biofouling B_2. As the shipper's reported liability share α_r increases, the shipper receives smaller ballast water subsidies, and as a result the shipper treats less B_1 and more B_2.

The results presented in panel d of Table 3 confirm that the shipper cannot increase its expected profit $E(\pi)$ by reporting a liability share α_r that differs from the shipper's true liability share α_t . As a result, it is assumed that the shipper will report its true liability share. The results in panel d indicate that as the shipper's true liability share increases, the shipper's expected profit decreases under the incentive mechanism.

The diagonal elements of panels b and c give the shipper's chosen values of B_1 and B_2 under the incentive mechanism, that is, when $\alpha_r = \alpha_t$. As the shipper's true liability share increases when under the incentive mechanism, the shipper's socially optimal selections of B_1 and B_2 do not change—the true liability share influences the distribution of rents between the firm and the rest of society, but it does not influence the determination of socially optimal activity levels.

Table 4
Solution values for the multiple externality model, with tax incentive mechanisms

Panel a—Tax and Fee values, t^*, F^*

α_r	0.5	0.75	0.99
t^*	0.57700	0.28850	0.01154
F^*	0.00411	0.00616	0.00813

Panel b—Ballast Water, $\bar{B}_1$

α_r	0.5	0.75	0.99
α_t			
0.5	0.53479	0.51648	0.49889
0.75	0.54701	0.53479	0.52307
0.99	0.55293	0.54367	0.53479

Panel c—Biofouling, $\bar{B}_2$

0.5	0.07123	0.10685	0.14104
0.75	0.04749	0.07123	0.09403
0.99	0.03598	0.05397	0.07123

Panel d—Shipper's expected profit, $E(\pi)$, per cubic meter

0.5	0.139945	0.139945	0.139945
0.75	0.138917	0.138917	0.138917
0.99	0.137931	0.137931	0.137931

Panel e—Expected social welfare, $E(W)$, per cubic meter

0.5	0.146110	0.145083	0.142163
0.75	0.145654	0.146110	0.145689
0.99	0.145103	0.145869	0.146110

As indicated by the results in panel a, in order to implement the incentive mechanism, the regulating port would have needed to pay the shipper a per-unit subsidy s of \$0.01–\$0.54 per cubic meter of ballast water emissions and a lump-sum subsidy S of \$0.02–\$0.04 per cubic meter.

Table 4 also contains 5 panels of results with a lump-sum tax and per unit tax. From panel a in Table 4, the taxes vary inversely as the per unit tax decreases, the lump-sum tax increases with the increased values of α_r . Values in panels b and c of Table 4 are similar to panels b and c of Table 3. Hence, the taxes work as do subsidies to encourage a balance between B_1 and B_2. The shipper has incentive to report a small liability share from biofouling damages. Hence a large per unit tax, is chosen because the shipper will otherwise choose a low level of hullfouling gleaning to discount the damages. As the reported value of α_r increases, the increase in liability for damages is enough incentive for the shipper to choose the optimal combination of hullfouling and ballast water.

Clearly there is a difference in welfare between the two sets of instruments. Panel d in Table 4 indicates a lower profit for the shipper facing taxes rather subsidies.

4. Conclusions

The results of this study show there is potential for a combination of incentive policies to help avoid marine invasive species in situations involving risk of damages and asymmetric information between ports and shippers.

The incentive policies can involve a combination of liability with subsidies or liability with taxes. The port's selected values of the two subsidies (a lump-sum and per cubic meter) vary inversely with one another to ensure that the shipper reports a true estimate of its invasive species damage liability. As the shipper's liability increases, the shipper's expected profit decreases under the incentive policy. However, when shipper's liability is high, a shipper regulated under the incentive policy earns higher profits than would an unregulated firm. Changes in liability do not affect the shipper's socially optimal selections of emission reduction—liability influences the distribution of rents between the shipper and the rest of society, but it does not influence the determination of socially optimal activity levels. The benefits of regulation to the shipper are higher when liability and invasive species damages are high. Alternatively, benefits of regulation in terms of social welfare are higher when liability and invasive species damages are low.

Although the subsidy-based policy achieves the (second-best) social optimum, there are alternative mechanisms such as taxes that achieve the same efficiency result with different equity outcomes. Under the tax-based policy, a per-unit tax of 0.5–28 cents per cubic meter in combination with a lump-sum fee of 0.05–0.10 cents (panel a, Table 4), depending on the shipper's multiple emissions vectors damage liability, result in the shipper's selection of the socially optimal combination of emissions reduction (compare panels b and c of Tables 3 and 4). Of course, under the tax-based policy, the shipper's profits are lower (compare panel d in Table 2 with panel d in Table 4), but expected social welfare remains the same (compare panel e in Table 3 with panel e in Table 4). The tax-based model shows that the same efficiency result can be achieved in alternative ways depending on equity goals and other constraints.

The model for the analysis draws on existing policy channels for potential regulatory action to formally address both shipping vectors of marine invasive species. The IMO guideline recommendation as the emission standard used in the model is presented in the mode of offering the flexibility to the shipper to be less or equal to the amount of emission allowed. Drawing on some measures of damages pertaining to biofouling meant that a distribution of damage risk was specified to derive analytical and numerical results. However, there are other aspects to the invasive species pollution problem that are truly uncertain where there would hardly be a risk probability distribution to specify. In some cases, such as with uncertainty in determining which shipper is at fault or uncertainties in the legal process, etc. which may prevent the shipper from bearing full financial responsibility for any damage, the parameter α makes sense in that it allows the possibility of a range rather than a point estimate to explore the variation in the liability policy with some uncertainty. However, with other aspects of uncertainty, the model would have to be stated with stochastic and general functional forms that may not have the definitive magnitudes in which to offer some of the interpretations found here with different policy options. This analysis can be viewed as offering a foundation for further analysis to ponder present and future policy options.

The implementation of the liability, subsidy and tax incentive policies can occur through existing but refined policies. Currently, the port fee for reporting ballast water filter and removal of emissions does not depend on the shipper's reported liability. However, this fee could be adjusted to correspond to the lump-sum fee in the tax-based incentive mechanism to induce the shipper to reveal its true liability. The subsidy for technology is not set according to a measure of actual impact of invasive species, and this amount could be modified to accomplish emission reductions of the analysis in order to properly address marine invasive species through both shipping emissions vectors. The recent US Commission on Ocean Policy suggests collecting adequate levels of resource rent for ocean space in terms of the port access fees that can be used to protect the public ocean (U.S. Commission on Ocean Policy, 2004). The tax mechanisms suggested here can serve towards this goal.

The purpose of the model presented here is to provide an illustration of how incentive mechanisms might be applied to "real-world" invasive species regulation. Rather than a focus on hypothetical policy, the existing channels for the incentive mechanisms are studied, thereby making it more plausible that the pollution problem can be addressed from the results. Refining current policy involves: (1) tying current technology subsidies of the US Coast Guard to liability; (2) tying current ballast water reporting fee to the port security liability rule; (3) ship registration liability under port security law post 2004 is more prominent and can help with environmental regulation of ships. US Senate Bill 770 Section 1.C mentions liability as a plausible policy to assign civil penalty for not addressing invasive species introductions related to shipping in the US Exclusive Economic Zone. The Invasive Species Specialist Group of the IUCN has called for the development of liability and criminal penalties for the consequence of unchecked, purposeful introductions of marine invasive species with responsibility for all costs associated with control, enforcement, and damages (Invasive Species Specialist Group, 2000).

The Ecological Society of America recommends actions that include focus on commercial shipping pathways, quantitative analysis, and study of incentives for cost-effective regulation. This research provides such action. The analytical method and policies apply to other settings beyond the Pacific Coast of North America by making appropriate modifications to choice variables, functional forms, sources of uncertainty and asymmetric information for those settings.

Appendix A

A.1. Case 2: Shipper profit maximization

$$\max_{B_1,B_2} E(\pi) = \int_0^\infty [r(B_1+B_2) - c_1B_1 \\ -c_2B_2 - \alpha DB_2^2] \cdot (\lambda e^{-\lambda t})\,dt \\ \text{s.t.} \quad a_1B_1 + a_2B_2 \leq \bar{I} \text{ (IMO pollution constraint).} \tag{9}$$

Solving the shipper's problem with methods analogous to those used in the port's problem, the shipper's profit-maximizing B_1 and B_2, denoted $\hat{B}_1$ and $\hat{B}_2$, are

$$\hat{B}_1 = \frac{M_1 + 2\alpha(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha(a_1/a_2)^2(1/\lambda)} \\ \hat{B}_2 = (\bar{I}/a_2) - (a_1/a_2)\hat{B}_1. \tag{10}$$

If the shipper's anticipated liability share $\alpha = 1$, that is, if the shipper expects to bear full liability for any and all multiple vector damage costs, then the unregulated shipper's choices of B_1 and B_2 correspond to the shipper's optimal values B_1^* and B_2^*.

The following maximization includes subsidies s and S as functions of α, that is, $s(\alpha)$ and $S(\alpha)$. The liability-regulated shipper's problem is to maximize expected profit, including any multiple vector damage liability, ballast water subsidy s, and lump-sum subsidy S, by choosing B_1

and B_2 subject to the IMO regulation constraint:

$$\begin{aligned}&\max_{B_1,B_2} E(\pi)=\int_0^\infty \big[r(\bar{B}_1+\bar{B}_2)-(c_1-s(\alpha_r))B_1\\&-c_2B_2-\alpha_t DB_2^2+S(\alpha_r)\big]\cdot(\lambda e^{-\lambda t})\,dt\\&\text{s.t.}\quad a_1B_1+a_2B_2\le \bar{I}\ (\text{IMO constraint}).\end{aligned}\tag{11}$$

Solving the IMO constraint for B_2 and substituting into the objective function:

$$\begin{aligned}&\max_{B_1} E(\pi)=\int_0^\infty \big[r(\bar{B}_1+\bar{B}_2)-(c_1-s(\alpha_r))B_1\\&-c_2\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}B_1\right)-\alpha_t D\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}B_1\right)^2+S(\alpha_r)\Bigg]\cdot(\lambda e^{-\lambda t})\,dt.\end{aligned}\tag{12}$$

The FOC for the problem is

$$\begin{aligned}\frac{\partial E(W)}{\partial B_1}&=\int_0^\infty\left[M_1+s(\alpha_r)+2\alpha_t D\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right)\right.\\&\qquad\left.-2\alpha_t D\left(\frac{a_1}{a_2}\right)^2B_1\right]\cdot(\lambda e^{-\lambda t})\,dt\equiv 0.\end{aligned}\tag{13}$$

Solving the regulated shipper's problem using methods analogous to those used in the social planner's problem, the regulated shipper's profit-maximizing values of B_1 and B_2, denoted $\bar{B}_1$ and $\bar{B}_2$, are given by

$$\begin{aligned}\bar{B}_1&=\frac{M_1+s(\alpha_r)+2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)}\\\bar{B}_2&=(\bar{I}/a_2)-(a_1/a_2)\bar{B}_1.\end{aligned}\tag{14}$$

The use of subsidies should result in $\bar{B}_1=B_1^*$ or

$$\begin{aligned}&\frac{M_1+s(\alpha_r)+2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)}\\&\quad=\frac{M_1+2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)},\end{aligned}$$

$$s(\alpha_r)=-(1-\alpha_r)\cdot M_1.\tag{15}$$

Since $M_1=r+c_2(a_1/a_2)-c_1$, the subsidy in the numerator would be adjusted according to α.

The shipper chooses α_r to maximize $E(\pi(\bar{B}_1,\bar{B}_2))$. Recalling expression (11) above, the shipper's problem is now

$$\begin{aligned}\max_{\alpha_r} E(\pi(\bar{B}_1,\bar{B}_2))&=\int_0^\infty\big[r(\bar{B}_1+\bar{B}_2)-(c_1-s(\alpha_r))\bar{B}_1\\&\qquad-c_2\bar{B}_2-\alpha_t D\bar{B}_2^2+S(\alpha_r)\big]\cdot(\lambda e^{-\lambda t})\,dt.\end{aligned}\tag{16}$$

Using the IMO constraint to substitute for $\bar{B}_2$, the shipper's problem becomes

$$\begin{aligned}&\max_{\alpha_r} E(\pi(\bullet)\int_0^\infty\Bigg[r\Big(\bar{B}_1+\Big(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\bar{B}_1\Big)\Big)-(c_1-s(\alpha_r))\bar{B}_1\\&-c_2\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\bar{B}_1\right)-\alpha_t D\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\bar{B}_1\right)^2+S(\alpha_r)\Bigg]\cdot(\lambda e^{-\lambda t})\,dt.\end{aligned}$$

The first-order condition for this problem is

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial\alpha_r}=&\int_0^\infty\Bigg[M_1\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}+\frac{\partial s}{\partial\alpha_r}\bar{B}_1+s\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&+\alpha_t M_2\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&-2\alpha_t M_3\bar{B}_1\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}+\frac{\partial S}{\partial\alpha_r}\Bigg]\\&\times(\lambda e^{-\lambda t})\,dt\equiv 0,\end{aligned}\tag{17}$$

where $M_2\equiv 2D(\bar{I}/a_2)(a_1/a_2)$, and $M_3\equiv D(a_1/a_2)^2$. Expression (17) implicitly defines the regulated shipper's profit-maximizing choice of α_r.

Verifying lump-sum subsidy S ensures $\alpha_r=\alpha_t$. To verify that a lump-sum subsidy S ensures $\alpha_r=\alpha_t$, it is sufficient to show that the shipper cannot increase profits by changing its reported value α from α_t to some other value α_r; that is, it is sufficient to show that

$$\left.\frac{\partial E(\pi(\bar{B}_1))}{\partial\alpha_r}\right|_{\alpha_r=\alpha_t}=0.\tag{18}$$

Substituting $\frac{\partial s}{\partial\alpha_r}=M_1\quad\frac{\partial\bar{X}_1}{\partial s}=\frac{1}{2\alpha_t(a_1/a_2)^2(1/\lambda)}$

$$\begin{aligned}\frac{\partial S(\alpha_r)}{\partial\alpha_r}=&\,c_1\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}-\frac{\partial s}{\partial\alpha_r}\bar{B}_1-s\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&-c_2\left(\frac{a_1}{a_2}\right)\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}-2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\\&\times\left(\frac{a_1}{a_2}\right)\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&+2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{r_1}{r_2}\right)^2\bar{X}_1\frac{\partial\bar{X}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&+\left(\frac{1}{\lambda}\right)\left(\left(\frac{\bar{I}}{r_2}\right)-\left(\frac{r_1}{r_2}\right)\bar{X}_1\right)^2-\frac{B_1^2}{4(r_1/r_2)^2(1/\lambda)}\end{aligned}$$

and the expressions for M_1, M_2, M_3, and $\bar{B}_1$ into eq. (17), yields

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial\alpha_r}=&\int_0^\infty\Bigg[2\alpha_t D\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&-2\alpha_t D\left(\frac{a_1}{a_2}\right)^2\bar{B}_1\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&-2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\\&+2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2\bar{B}_1\frac{\partial\bar{B}_1}{\partial s}\frac{\partial s}{\partial\alpha_r}\Bigg]\cdot(\lambda e^{-\lambda t})\equiv 0.\end{aligned}$$

Carrying-out integration (via the methods of u-substitution and integration by parts),

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_r} &= 2\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}\\ &\quad - 2\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2\bar{B}_1\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}\\ &\quad - 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}\\ &\quad + 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2\bar{B}_1\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} \equiv 0.\end{aligned}$$

Evaluating the last expression above for $\alpha_r = \alpha_t$ verifies that

$$\left.\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_r}\right|_{\alpha_r=\alpha_t} = 0.$$

Then, the incentive is viewed as incentive compatible and individually rational for the shipper.

The port's choice of lump-sum subsidy S: Under the assumption that the lump-sum subsidy S ensures that $\alpha_r = \alpha_t$, the regulated shipper's expected profit $E(\pi(\bar{B}_1))$ varies with its *true* liability share α_t as

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_t} = \int_0^\infty \Bigg\{ & M_1\left[\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \bar{B}_1}{\partial \alpha_t}\right] + \frac{\partial s}{\partial \alpha_t}\bar{B}_1\\ & + s\left[\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \bar{B}_1}{\partial \alpha_t}\right] + M_2\bar{B}_1\\ & + \alpha_t M_2\left[\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \bar{B}_1}{\partial \alpha_t}\right]\\ & - M_3\bar{B}_1^2 - 2\alpha_t M_3\bar{B}_1\left[\frac{\partial \bar{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \bar{B}_1}{\partial \alpha_t}\right]\\ & - D(\bar{I}/a_2)^2 + \frac{\partial S}{\partial \alpha_t}\Bigg\}\cdot\left(\lambda e^{-\lambda t}\right)dt. \qquad (19)\end{aligned}$$

As the lump-sum subsidy S (derived below) ensures that $\alpha_r = \alpha_t$ (as verified in Appendix A), (17) helps simplify (19) via the envelope theorem yielding:

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_t} = \int_0^\infty \Bigg\{ & -D(\bar{I}/a_2)^2 + M_1\left[\frac{\partial \bar{B}_1}{\partial \alpha_t}\right]\\ & + s\left[\frac{\partial \bar{B}_1}{\partial \alpha_t}\right] + M_2\bar{B}_1 + \alpha_t M_2\left[\frac{\partial \bar{B}_1}{\partial \alpha_t}\right]\\ & - M_3\bar{B}_1^2 - 2\alpha_t M_3\bar{B}_1\left[\frac{\partial \bar{B}_1}{\partial \alpha_t}\right]\Bigg\}\\ & \times\left(\lambda e^{-\lambda t}\right)dt. \qquad (20)\end{aligned}$$

From Section 2.2.4, it follows that

$$\frac{\partial \bar{B}_1}{\partial \alpha_t} = \frac{-M_1}{2\alpha_t(a_1/a_2)^2(1/\lambda)}.$$

Hence, expression (20) becomes

$$\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_t} = \int_0^\infty \left\{\frac{DM_1^2 - 2M_1^2(1/\lambda)}{4(a_1/a_2)^2(1/\lambda)^2}\right\}\cdot\left(\lambda e^{-\lambda t}\right)dt \qquad (21)$$

or

$$\begin{aligned}\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_t} = \left(\frac{M_1^2}{4(a_1/a_2)^2}\right)\int_0^\infty & \left\{\frac{D}{(1/\lambda)^2}\right\}\\ & \times\left(\lambda e^{-\lambda t}\right)dt - \left(\frac{M_1^2}{2(a_1/a_2)^2}\right)\int_0^\infty \{\lambda\}\\ & \times\left(\lambda e^{-\lambda t}\right)dt.\end{aligned}$$

Evaluating the left-hand integral in the expression above via the method of integration by parts (with $u = D$ and $v = -e^{-\lambda t}$), and the right-hand integral via the method of u-substitution (with $u = -\lambda D$), leaves

$$\frac{\partial E(\pi(\bar{B}_1))}{\partial \alpha_t} = \frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}. \qquad (22)$$

The portion of $E(\pi(\bar{B}_1))$ that varies with α contains the following terms:

$$\begin{aligned}&\int_0^\infty \Bigg[(r - c_1 - s(\alpha_r))\bar{B}_1 - c_2\left(-\frac{a_1}{a_2}\bar{B}_1\right)\\ &-\alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\bar{B}_1\right)^2 + S(\alpha_r)\Bigg]\cdot\left(\lambda e^{-\lambda t}\right)dt. \qquad (23)\end{aligned}$$

Expression (23) is equal to the integral of expression (22) multiplied by the density function of α, $p(\alpha)$, where $p(\alpha)$ is uniformly distributed over support (0,1), based on the description of liability under shipping rules facing limited liability as well as joint and several liability that yields a flexible range of possible outcomes. The integral is taken over α from $\alpha = 0$ to $\alpha = \alpha_t$, that is

$$\begin{aligned}&\int_0^\infty \Bigg[(r - c_1 - s(\alpha_r))\bar{B}_1 - c_2\left(-\frac{a_1}{a_2}\bar{B}_1\right)\\ &-\alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\bar{B}_1\right)^2 + S(\alpha_r)\Bigg]\cdot\left(\lambda e^{-\lambda t}\right)dt\\ &= \int_0^{\alpha_t}\frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}\cdot p(\alpha)\,d\alpha \qquad (24)\end{aligned}$$

Evaluating the integral on the left-hand side of expression (24), and recalling that $p(\alpha) = 1/(1-0)$ for a uniform distribution with support (0,1), expression (24) becomes:

$$\begin{aligned}&r - (c_1 - s(\alpha_r))\bar{B}_1 + c_2\left(\frac{a_1}{a_2}\right)\bar{B}_1\\ &\quad - \alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\bar{B}_1\right)^2\\ &\quad + S(\alpha_r)\int_0^{\alpha_t}\frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}\cdot\left[\frac{1}{1-0}\right]d\alpha.\end{aligned}$$

Evaluating the integral on the right-hand side of the expression above, yields

$$
\begin{aligned}
&-(c_1 - s(\alpha_r))\bar{B}_1 + c_2\left(\frac{a_1}{a_2}\right)\bar{B}_1 \\
&\quad -\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\bar{B}_1\right)^2 \\
&\quad + S(\alpha_r) = \frac{-M_1^2\alpha_t}{4(a_1/a_2)^2(1/\lambda)},
\end{aligned}
\tag{25}
$$

from which the port's rule for determining the lump-sum subsidy S as a function of the shipper's reported value of α is recovered:

$$
\begin{aligned}
S(\alpha_r) = {}&(-r + c_1 + s(\alpha_r))\bar{B}_1 \\
&- c_2\left(\frac{a_1}{a_2}\right)\bar{B}_1 + \alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\bar{B}_1\right)^2 \\
&- \frac{M_1^2\alpha_r}{4(a_1/a_2)^2(1/\lambda)}.
\end{aligned}
\tag{26}
$$

The regulated shipper's expected profit $E(\pi(\bar{B}_1))$ *under the incentive mechanism:* The regulated shipper's expected profit under the incentive mechanism $E(\pi(\bar{B}_1))$ is found by adding the portion of $E(\pi(\bar{B}_1))$ that varies with α, equivalent to the right-hand side of expression (25), to the portion of $E(\pi(\bar{B}_1))$ that does *not* vary with α, namely $r-(c_2\bar{I}/a_2)$:

$$
E(\pi(\bar{B}_1)r - (c_2\bar{I}/a_2) - \frac{M_1^2\alpha_t}{4(a_1/a_2)^2(1/\lambda)}.
$$

For each following section, the results of the analysis are similar to the per unit lump-sum subsidy analysis with the difference that fees represent an additional cost and subsidies, a reduction in costs.

The regulating port's problem: The regulating port's problem under tax regulation is identical to that under subsidy regulation and produces identical results B_1^*, B_2^*.

The shipper's problem: The unregulated shipper's problem under tax regulation is identical to that under subsidy regulation and produces identical results: B_1^*, B_2^*. As the unregulated shipper's anticipated liability share α decreases from its maximum value of 1, $\hat{B}_1$ decreases and $\hat{B}_2$ increases, deviating from their socially-optimal values B_1^*, B_2^*.

$$
\begin{aligned}
\max_{B_1,B_2} E(\pi) = {}&\int_0^\infty [r - c_1B_1 - (c_2 + t(\alpha_r))B_2 \\
&-\alpha_t DB_2^2 - F(\alpha_r)]\cdot(\lambda e^{-\lambda t})\,\mathrm{d}t \\
\text{st.}\quad & a_1B_1 + a_2B_2 = \bar{I}\ (\text{IMO constraint}).
\end{aligned}
\tag{27}
$$

Solving the constraint for B_1 and substituting into the objective function:

$$
\begin{aligned}
\max_{B_2} E(\pi) = {}&\int_0^\infty \left[r - c_1\left(\frac{\bar{I}}{a_1}-\frac{a_2}{a_1}B_2\right)\right. \\
&\left.-(c_2 + t(\alpha_r))B_2 - \alpha_t DB_2^2 - F(\alpha_r)\right] \\
&\times\left(\lambda e^{-\lambda t}\right)\mathrm{d}t.
\end{aligned}
\tag{28}
$$

The FOC for the problem is

$$
\begin{aligned}
\frac{\partial E(\pi)}{\partial B_2} = {}&\int_0^\infty [M_4 - t(\alpha_r) - 2\alpha_t DB_2] \\
&\times\left(\lambda e^{-\lambda t}\right)\mathrm{d}t \equiv 0, \\
&\text{where } M_4 \equiv r + c_1a_2/a_1 - c_2.
\end{aligned}
\tag{29}
$$

Evaluating the integral in (29) using methods analogous to previous sections, the resulting expression for the shipper's profit-maximizing values of B_1 and B_2 is solved under tax regulation, denoted $\dddot{B}_1$ and $\dddot{B}_2$:

$$
\begin{aligned}
\dddot{B}_2 &= \frac{M_4 - t(\alpha_r)}{2\alpha_t(1/\lambda)}, \\
\dddot{B}_1 &= (\bar{I}/a_1) - (a_2/a_1)\dddot{B}_2.
\end{aligned}
\tag{30}
$$

The port's choice of per-unit tax t: The port determines the per unit tax $t(\alpha_r)$ necessary to ensure that $\dddot{B}_2 = B_2^*$ under the assumption that the lump-sum fee $F(\alpha_r)$ (derived below) will ensure that $\alpha_r = \alpha_t$:

$$
\begin{aligned}
&\dddot{B}_2 = B_2^*, \\
&\frac{M_4 - t(\alpha_r)}{2\alpha_t(1/\lambda)} = \frac{M_4}{2(1/\lambda)}, \\
&t(\alpha_r) = (1-\alpha_r)\cdot M_4.
\end{aligned}
\tag{31}
$$

The per unit tax is similar to the form of the per unit subsidy.

The shipper's choice of reported liability α_r*:* The regulated shipper knows that the port's per unit tax rule $t(\alpha_r)$ and lump-sum fee $F(\alpha_r)$ depend on the shipper's report α_r. The regulated shipper chooses α_r to maximize $E(\pi(\dddot{B}_1, \dddot{B}_2))$. Through the first order necessary condition derived from Eq. (28) above:

$$
\begin{aligned}
\max_{\alpha_r} E(\pi(\dddot{B}_1(\dddot{B}_2), \dddot{B}_2)) = {}&\int_0^\infty \left[r - c_1\left(\frac{\bar{I}}{a_1}-\frac{a_2}{a_1}\right.\right. \\
&\left.\times\dddot{B}_2(s(\alpha_r), \alpha_t)\right) \\
&-(c_2 + t(\alpha_r)) \\
&\times\dddot{B}_2(s(\alpha_r), \alpha_t) \\
&\left.-\alpha_t D\left(\dddot{B}_2(s(\alpha_r), \alpha_t)\right)^2 - F(\alpha_r)\right] \\
&\times\left(\lambda e^{-\lambda t}\right)\mathrm{d}t.
\end{aligned}
\tag{32}
$$

The first-order condition for this problem is

$$\frac{\partial E(\pi(\ddot{B}_2))}{\partial \alpha_r} = \int_0^\infty \left[M_4 \frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_r} - \frac{\partial t}{\partial \alpha_r} \dddot{B}_2 \right. \\ \left. - t \cdot \frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_r} - 2\alpha_t D \dddot{B}_2 \frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_r} - \frac{\partial F}{\partial \alpha_r} \right] \\ \times \left(\lambda e^{-\lambda t} \right) dt \equiv 0. \tag{33}$$

$$\frac{\partial E(\pi)}{\partial \alpha_t} = \int_0^\infty \left\{ M_4 \left[\frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] \right. \\ - \frac{\partial t}{\partial \alpha_t} \dddot{B}_2 - t \cdot \left[\frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] \\ - 2\alpha_t D \dddot{B}_2 \left[\frac{\partial \dddot{B}_2}{\partial t} \frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] \\ \left. - D \dddot{B}_2^2 - \frac{\partial F}{\partial \alpha_t} \right\} \cdot \left(\lambda e^{-\lambda t} \right) dt. \tag{34}$$

As the lump-sum fee F (derived below) ensures that $\alpha_r = \alpha_t$, we may use (33) to simplify (34) via the envelope theorem to find

$$\frac{\partial E(\pi)}{\partial \alpha_t} = \int_0^\infty \left\{ M_4 \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] - t \cdot \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] \right. \\ \left. - 2\alpha_t D \dddot{B}_2 \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t} \right] - D \dddot{B}_2^2 \right\} \\ \times \left(\lambda e^{-\lambda t} \right) dt. \tag{35}$$

Recognizing that

$$\frac{\partial \dddot{B}_2}{\partial \alpha_t} = \frac{-M_4}{2\alpha_t^2 (1/\lambda)},$$

and evaluating the integral in expression (35) using methods analogous to those in Section 2.2.1, yields

$$\frac{\partial E(\pi)}{\partial \alpha_t} = \frac{-M_4^2}{4(1/\lambda)}. \tag{36}$$

Define *the portion of E(π) that varies with α* as

$$\int_0^\infty \left[c_1 (a_2/a_1) \dddot{B}_2 - (c_2 + t(\alpha_t)) \dddot{B}_2 \right. \\ \left. - \alpha_t D \dddot{B}_2^2 - F(\alpha_r) \right] \cdot \left(\lambda e^{-\lambda t} \right) dt. \tag{37}$$

Expression (37) is equal to the integral of expression (36) multiplied by the density function of α, $p(\alpha)$, where $p(\alpha)$ is uniformly distributed over support (0,1), and where the integral is taken over α from $\alpha = 0$ to $\alpha = \alpha_t$, that is,

$$\int_0^\infty \left[c_1 (a_2/a_1) \dddot{B}_2 - (c_2 + t(\alpha_t)) \dddot{B}_2 \right. \\ \left. - \alpha_t D \dddot{B}_2^2 - F(\alpha_r) \right] \cdot \left(\lambda e^{-\lambda t} \right) dt$$

$$= \int_0^{\alpha_t} \frac{-M_4^2}{4(1/\lambda)} \cdot p(\alpha)\, d\alpha \\ = \int_0^{\alpha_t} \frac{-M_4^2}{4(1/\lambda)} \cdot \left[\frac{1}{1-0} \right] d\alpha \\ = \left. \frac{-M_4^2 \alpha}{4(1/\lambda)} \right|_0^{\alpha_t} = \frac{-M_4^2 \alpha_t}{4(1/\lambda)}. \tag{38}$$

After evaluating the integral on the left-hand side of (38), the regulating port's rule for determining the fixed fee F as a function of the shipper's reported value of α is found:

$$F(\alpha_r) = c_1 (a_2/a_1) \dddot{B}_2 - (\tilde{c}_2 + t(\alpha_r)) \dddot{B}_2 \\ - \alpha_r (1/\lambda) \dddot{B}_2^2 + \frac{M_4^2 \alpha_r}{4(1/\lambda)}. \tag{39}$$

The regulated shipper's expected profit E(π) under the incentive mechanism: The regulated shipper's expected profit under the incentive mechanism $E(\pi(\ddot{B}_2))$ is found by adding *the portion of E(π) that varies with α*, equivalent to the right-hand side of expression (38), to *the portion of E(π) that does not vary with α*, namely $r - (c_1 \bar{I}/a_1)$:

$$E(\pi(\dddot{B}_2)) = r - (c_1 \bar{I}/a_1) - \frac{M_4^2 \alpha_t}{4(1/\lambda)}. \tag{40}$$

This profit should be lower than the subsidy case.

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A two-agent dynamic model with an invasive weed diffusion externality: An application to Yellow Starthistle (*Centaurea solstitialis L.*) in New Mexico

Kristine M. Grimsrud*, Janie M. Chermak, Jason Hansen, Jennifer A. Thacher, Kate Krause

Department of Economics, University of New Mexico, MSC05 3060, Albuquerque, NM 87131, USA

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Abstract

This paper presents a bioeconomic model for two agents, a cattle rancher and a non-rancher, with interdependencies between their individual effort of invasive weed management and profitability. Dynamic simulations allow us to find numerically the optimal effort of weed control over a 5-year time horizon under a variety of beginning infestation levels. In a base-case scenario without governmental cost-share of control costs, we find that efforts to control the weed are not profitable. The base-case scenarios also indicate that grazing contributes to giving the invasive weed a competitive edge. A second series of simulations include incentive payments for weed control which are set at the minimum level required to have a net positive impact on the rancher's profitability. From these simulations, we find that the level of infestation impacts the size of the incentive necessary to get the agent to control the weeds and that the incentive payments impact the level of effort of the rancher. In addition, results reveal that the higher incentive payments for lower levels of weed infestations reduce the total cumulative incentive payments over time. Efficient policies directed towards management of invasive weeds may need to be adjusted for each individual case.

Keywords: Invasive species; Dynamic externality; Yellow starthistle

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1. Introduction

Invasive alien weeds (IAW) are a costly problem for US agriculture. Pimentel et al. (2005) estimate IAW costs US agriculture \$27 billion annually, consisting of \$24 billion in crop losses and \$3 billion in herbicide treatment costs. In many cases, by the time an IAW poses an economic problem or threat, it is well established and prevention is no longer an option. Successful prevention and early detection may well be the best management strategies. To be successful, such strategies need to be economically feasible for private producers and implemented prior to the critical level establishment of the species. Actions today that guard against the establishment of a species or that control the species, while increasing the current cost of operations, will have realized benefits at some point in the future. The trade-off is between current weed control and future productivity of the land. A second complication is that even if one agent efficiently controls or eradicates the weed on her particular plot, there is always the potential for increased weed infestation or re-infestation as a result from neighboring and more distant land infested with the weed. Thus, the invasive weed problem can be considered a dynamic externality (see, e.g. Levhari and Meriman, 1980).

We present a bioeconomic model for an invasive weed problem with diffusion between neighbors. The model combines the biologic responses of an invasive weed and grasses with the weed diffusion externalities between pasture owners within a dynamic framework. Assuming a profit-maximizing objective, the individual rancher knows that her outcome depends on her individual decisions to control the weed as well as characteristics and decisions made by other ranchers and the biologic specifics of the invasive species. Characteristics of the invasive weed include its growth and carrying capacity, the degree to

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*Corresponding author. Tel.: +1 505 277 1960; fax: +1 505 277 9445.
E-mail address: grimsrud@unm.edu (K.M. Grimsrud).

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which it can reduce the productivity by competing out grasses, dispersal rate, and mode.[1]

The following section presents a brief literature review. Section 3 derives a general economic model for the problem. In Section 4, specific functional forms related to the Yellow Starthistle (*Centaurea solstitialis L.*) weed problem are presented. Section 5 finds numerically the optimal effort levels for a rancher when the model is parameterized for Yellow Starthistle invasion in New Mexico. Section 6 closes with conclusion.

2. Previous work

Much of the literature on invasive species focuses on the optimal levels of effort in preventing an invasive from becoming established or on the optimal level of control once an invasive has become established (Eiswerth and Johnson, 2002; Horan et al., 2002; Olson and Roy, 2002; Settle and Shogren, 2002). Pitafi and Roumasset (2006) present an integrated theoretical model of optimal prevention and control; they embed the solution to the control problem within the optimal prevention problem. Their argument is that these are not separate decisions and that the optimal level of prevention effort depends on the costs associated with control after establishment. Their model predicts that prevention expenditures will increase with increases in control or damage costs, lower interest rates, or more effective prevention methods.

McKee (2006) examines the case where production decisions by an agricultural producer affect producers with adjoining fields, thus causing an externality. Specifically, he examines the situation where planting and harvesting decisions by one producer of a crop that hosts an invasive (the greenhouse whitefly), causes the invader to migrate to adjoining fields and impact strawberries. The paper finds that in certain cases, profits for strawberry producers is higher with regional management of the invasive than it is with private, single-field management; the optimal timing of pesticide application can vary depending on when other host crop producers harvest their crops. Regional management among producers requires limited and relatively inexpensive coordination: the sharing of crop harvest information among host crop producers.

Cacho et al. (2004) compare the net benefits for attempting eradication or doing nothing, when a weed is discovered. Factors affecting the net benefit include: the size of the invaded area, the rate of spread of the weed, the longevity of the seed-bank, the benefits from current land use, and the cost of potential control options. They identify two points, based on the size of the invasion, where it is no longer optimal to attempt eradication or to attempt any form of control. The application is to Scotch broom. Seed-bank longevity was the most important factor in determining the feasibility of eradication.

Eiswerth and van Kooten (2002) present a dynamic model that incorporates uncertainty about data and variables in the model. The application is to Yellow Starthistle (*Centaurea solstitialis L.*) rangeland in California. They survey a group of experts in order to obtain transition probabilities and the impact of Yellow Starthistle on grazing and on pasture hay production. They examine competing control strategies for three different types of land uses (grazing on rangeland, grazing on pastureland, and harvest of hay from pastureland) and find that control strategies rather than eradication are optimal. There are no neighbor interaction effects in the model.

We extend the literature by considering the impact of interaction between two agents under different levels of infestation of Yellow Starthistle. We consider two types of land-use (grazing on rangeland and non-grazed pastureland) and focus on the impact of initial efforts of the agents, whose actions impact the other agents by diffusion of the weed, under varying initial levels of infestation. We begin by formulating a general model for the problem and use it to discuss some general implications for optimal choices of effort levels.

3. Economic model

Consider two ranchers, hereafter, agents, i and j, whose adjacent plots of land are both infested with invasive weeds. Agent i produces beef using pasture land for grazing. Agent j may either be a beef producer or one of several different types of land-owners, including a land owner who does not utilize the pasture land in any agricultural production.

Weeds w_{it} and grasses g_{it} in the agents' pastures compete for resources such as light, water and nutrients. The competitiveness of weeds is strengthened as cattle selectively eat grasses and avoid weeds. Thus the growth of the stock of grasses $G(g_{it},w_{it})$ in discrete time is modeled as a function of the density of both grasses and weeds. In the first time period, agent i places a stock of cattle $s_i(t=0)=s_{i0}$ expressed in pounds per acre[2] on the pasture. Let s_{ci} (lbs/ac) equal the carrying capacity or maximum pounds of cattle per acre that the pasture can support, and let the amount of forage or grasses available on the pasture in the first season be denoted by g_{i0} (lbs/ac). The stock placed on the pasture in the first time period is determined by:

$$s_{i0}=\begin{cases} s_{ci}g_{i0}/K_{gi} & \text{if } 0<g_{i0}/K_{gi}<1,\\ s_{ci} & \text{if } g_{i0}/K_{gi}=1, \end{cases} \tag{1}$$

where K_{gi} (lbs/ac) equals the carrying capacity of grasses on the pasture. That is, if initial grass density, i.e. grasses available, g_{i0}, is equal to the carrying capacity for grasses of the pasture, K_{gi}, then the initial stock of cattle s_{i0} equals the

---

[1] Mode here refers to the method the species uses to disperse seeds, e.g. some plants target birds, wind, or water for their seed dispersal.

[2] This unit of measurement for the stock of cattle is consistent with market practices where cattle are sold by weight and allows us to model the rancher's choice variable as effort level rather than number of heads of cattle to place on the pasture.

carrying capacity of the pasture for cattle, s_{ci}. However, if $g_{0i} < K_{gi}$, rancher i will place a proportionally smaller stock of cattle on the pasture in the initial time period. In the following time periods, the weight increase of the initial stock of cattle is related to the density of grasses by $s_{it} = s(g_{it}) = mf(g_{it})$ where $f(g_{it})$ the amount of grass consumed (lbs/ac) and m is the percent weight gain associated with consuming a unit of grass. As a result, the per period change in stock of pasture grasses is given by:

$$g_{it+1} - g_{it} = G(g_{it}, w_{it}) - f(g_{it}). \tag{2}$$

The growth of weeds in the pasture is also modeled as depending on both the density of grasses and weeds, $W(g_{it}, w_{it})$ since grasses compete with weeds. Invasive weeds are less valuable as cattle feed or even inedible or toxic to livestock, and reduce the carrying capacity of the pasture in terms of the weight of cattle supported per acre. As a result, ranchers have an incentive to remove these weeds. The percentage removal of weeds per acre as a function of effort e_{it} is modeled as $r(e_{it})$ and the total removal is given by $r(e_{it})w_{it}$ where $r'(e_{it}) \geqslant 0$. Ignoring neighbor spill-over effects, agent i will chose effort levels based on several factors including the characteristics of the weed, the level of infestation, productivity of the pasture and economic parameters.

Weeds are added to agent i's land by short-distance diffusion between the two neighboring agents i and j and by long-distance diffusion between agent i's plot of land and the overall community. The dominant vectors for short-distance diffusion are wind, water, animals, and movement of people, vehicles, and transport of equipment (Levin et al., 2003) between agents i and j. Long-distance diffusion-vectors are generally related to human activity. Some examples include trade and transport of grasses and hay contaminated by weeds, contamination via vehicles, equipment, and recreationists, and trade and transport of animals. Birds are responsible for both short- and long-distance diffusion when they feed on seed and the seeds are still viable after passing through the digestive tract (Levin et al., 2003). Because weeds may diffuse from one plot of land to another, agent i will also take into consideration the effort and weed levels observed on agent j's adjacent land. In addition, agent i is affected by diffusion from the surrounding community $\bar{w}_t$. The diffusion from surrounding land, including agent j's land, is given as $d(w_{jt}(e^*_{jt}(e_{it}, w_{it})), \bar{w}_t)$ where $(\partial d/\partial w_{jt}) > 0$, $(\partial w_{jt}/\partial e^*_{jt}) < 0$, and $e^*_{jt}(e_{it}, w_{it})$ is a reaction function modeling the optimal level of effort for agent j as a function of rancher i's effort level and weed infestation level. The reaction function assumes that agent j has full information about agent i's effort; the asterisk signifies that agent j chooses effort optimally. The sign of $\partial e^*_{jt}/\partial e_{it}$ depends on whether agent j adopts a collaborative $(\partial e^*_{jt}/\partial e_{it}) > 0$ or a free-riding strategy $(\partial e^*_{jt}/\partial e_{it}) < 0$. The optimal efforts of agent j will also depend on the weed levels on agent i's plot of land through the term $\partial e^*_{jt}/\partial w_{it}$. The sign of this term likely depends on the characteristics of agent j's ranch, such as size of operation. For instance, a smaller producer or a part-time producer may choose to expend less effort as weeds on agent i's parcel increase while a large, full time producer may have more resources and economic interest in keeping weeds on his/her parcel at a low level. In that case the sign of $\partial e^*_{jt}/\partial w_{it}$ would be positive. Accounting for growth, weed removal and diffusion, the per time period change in the stock of weeds on agent i's pasture is given by:

$$w_{it+1} - w_{it} = W(g_{it}, w_{it}) - r(e_{it})w_{it} + d(w_{jt}(e^*_{jt}(e_{it}, w_{it})), \bar{w}_t). \tag{3}$$

The net benefits at time t for agent i, $V(s_{it}, e_{it})$, are a function of the benefits of the weight increase of the stock of cattle per time period $s_{it} = s(g_{it})$ which is a direct function of the amount of grass consumed. The benefits of weed removal efforts enter the net benefits function through the increased grass availability that is possible when weeds are removed. The benefits of beef production are balanced by the cost of beef production and the cost of effort for weed removal. A basic model for the problem of choosing an effort level when the weeds represent a dynamic externality may be formulated as:

$$\max_{e_{it}} \quad A \sum_{t=0}^{T-1} \rho^t V(s(g_{it}), e_{it}), \tag{4a}$$

$$g_{it+1} - g_{it} = G(g_{it}, w_{it}) - f(g_{it}), \tag{4b}$$

$$w_{it+1} - w_{it} = W(g_{it}, w_{it}) - r(e_{it})w_{it} + d(w_{jt}(e^*_{jt}(e_{it}, w_{it})), \bar{w}_t). \tag{4c}$$

$$g_i(t=0) = g_{i0} \quad \text{and} \quad w_i(t=0) = w_{i0}. \tag{4d}$$

where A is the acreage of the farm, $\rho = (1+\delta)^{-1}$ is the discount factor and Eq. (4d) describes initial conditions. The Lagrangian for the model in Eq. (4a)–(4d) is:

$$\begin{aligned} L = \sum_{t=0}^{T-1} \rho^t \{ & V(s(g_{it}), e_{it}) \\ & + \rho\lambda_{t+1}[g_{it} - g_{it+1} + G(g_{it}, w_{it}) - f(g_{it})] \\ & + \rho\mu_{t+1}[w_{it} - w_{it+1} + W(g_{it}, w_{it}) - r(e_{it})w_{it} \\ & + d(w_{jt}(e^*_{jt}(e_{it}, w_{it})), \bar{w}_t)]\}. \end{aligned} \tag{5}$$

Given a unique, interior (incomplete eradication) optimal trajectory of grass, weed and effort levels the first order conditions are given by (see e.g. Conrad, 1999):

$$\frac{\partial L}{\partial e_{it}} = 0 \Rightarrow \frac{\partial V}{\partial e_{it}} = \rho\mu_{t-1}\left(r'(e_{it})w_{it} - \frac{\partial d}{\partial w_{ij}} \frac{\partial w_{jt}}{\partial e^*_{jt}} \frac{\partial e^*_{jt}}{\partial e_{it}} \right), \tag{6a}$$

$$\begin{aligned} -\frac{\partial L}{\partial g_{it}} = \rho\lambda_{t+1} - \lambda_t \Rightarrow \rho\lambda_{t+1} - \lambda_t & \\ = -\frac{\partial V}{\partial s_{it}} \frac{\partial s_{it}}{\partial g_{it}} - \rho\lambda_{t+1}\left(\frac{\partial G}{\partial g_{it}} - \frac{\partial f}{\partial g_{it}} \right) & \\ - \rho\mu_{t+1} \frac{\partial W}{\partial g_{it}}, & \end{aligned} \tag{6b}$$

$$-\frac{\partial L}{\partial w_{it}} = \rho\mu_{t+1} - \mu_t \Rightarrow \rho\mu_{t+1} - \mu_t$$
$$= -\rho\lambda_{t+1}\frac{\partial G}{\partial w_{it}} - \rho\mu_{t+1} \times \left(\frac{\partial W}{\partial w_{it}} - r(e_{it}) + \frac{\partial d}{\partial w_{jt}}\frac{\partial w_{jt}}{\partial e^*_{jt}}\frac{\partial e^*_{jt}}{\partial w_{it}}\right), \tag{6c}$$

$$\frac{\partial L}{\partial \lambda_t} = 0 \Rightarrow g_{it+1} - g_{it} = G(g_{it}, w_{it}) - f(g_{it}), \tag{6d}$$

$$\frac{\partial L}{\partial \mu_t} = 0 \Rightarrow w_{it+1} - w_{it} = W(g_{it}, w_{it}) - r(e_{it})w_{it} + d(w_{jt}(e^*_{jt}(e_{it}, w_{it})), \bar{w}_t). \tag{6e}$$

Condition (6a) states that the marginal impact on benefits with respect to effort (which is negative since efforts are costly) equals the value of weed removal ($r'(e_{it}) \geqslant 0$) minus value of the marginal change in diffusion from agent j's land to agent i's land. The multiplier of the weed transition equation, μ_t, is always negative since weeds contribute to reduced net benefits. The sign of effort impact on the diffusion-term in (6a) determines whether agent i will increase or decrease her effort when weed levels increase on agent j's pasture. Notice that $\partial d/\partial w_{jt}$ is always positive: the more weeds there are on agent j's pasture, the greater the diffusion, and that $\partial w_{jt}/\partial e^*_{jt}$ is always negative: effort reduces weeds.

Further knowledge of the sign of $\partial e^*_{jt}/\partial e_{it}$ is necessary to determine whether the marginal change in diffusion as a result of agent i's effort is positive, zero or negative. If $\partial e^*_{jt}/\partial e_{it} = 0$, there is no relationship between agent i and agent j's choice of effort. If $\partial e^*_{jt}/\partial e_{it} < 0$, then agent j reduces effort as agent i increases effort, in other words, agent j freerides on agent i's effort. In this case, the second term on the right-hand side of Eq. (6a) is positive overall. When subtracted from the first right-hand side term, agent j's freeriding causes the marginal benefits of weed removal for agent i to decline. The marginal cost of effort on weed removal also has to be reduced for Eq. (6a) to hold. In sum, if agent j freerides, agent i will have reduced benefits of weed removal and will thus reduce her effort. On the other hand, if $\partial e^*_{jt}/\partial e_{it} > 0$ agent j will increase effort on weed removal if agent i increase her effort, i.e. the agents collaborate. In this case the second right-hand side term of Eq. (6a) is negative. The marginal benefits of agent i's weed removal are increased and agent i will as a result increase efforts on weed removal.

First order condition (6b) dictates that the change in present value of grass over time equals the marginal value of grass in production of beef, the marginal value of grass in producing more grass and the marginal value of grass in competing with weeds. The marginal value of grass in time t in producing more grass in time $t+1$ is adjusted by feeding. If the growth function of grass is characterized by density dependent growth, then feeding will reduce crowding if the stock of grass approaches carrying capacity, while feeding will inhibit growth as the stock of grass moves closer to zero. Eq. (6c) states that the losses caused by the weed stock over time equal the marginal value of reduced production of grass caused by competition, the marginal value of the contribution of weeds to own growth adjusted for weed removal and the marginal value of the change in diffusion. The marginal value of change in diffusion can be either positive, zero or negative depending on the sign of $\partial e^*_{jt}/\partial w_{it}$. If $\partial e^*_{jt}/\partial w_{it} = 0$ then the efforts of agent j are not affected by the weed levels on agent i's land and the marginal value of change in diffusion is zero. If $\partial e^*_{jt}/\partial w_{it} < 0$ agent j will decrease efforts as weed levels increase on agent i's plot of land. Then the marginal value of change in diffusion is negative overall and the losses caused by the weed infestation increase. On the other hand, if the sign of $\partial e^*_{jt}/\partial w_{it}$ is positive, agent j increases efforts as weed levels increase on agent i's land, and losses caused by weed infestation decrease. The last two first order conditions, Eqs. (6d) and (6e) returns the transition equations for grasses and weeds.

In the following discussion, we define functional forms for the model in Eqs. (4a)–(4d), before we proceed to parameterize the model for Yellow Starthistle for the case of New Mexico and solve numerically for optimized effort levels.

4. Specification of empirical optimization model for Yellow Starthistle in New Mexico

Yellow Starthistle (hereafter YST) is a Eurasian knapweed that was first documented in California in 1824, where it was accidentally introduced via alfalfa seed. YST has been found in 41 states in the United States and is classified as a noxious weed by 12 states. In 1996, YST infested about 10 million acres concentrated in California, Oregon, Idaho, and Washington (Thomsen et al., 1996). By 2006 YST had invaded more than 14 million acres in California alone—14% of the land area of the state (Western Farmpress, 2006). YST has also begun to invade rangeland in New Mexico and can currently be found in six counties (USDA NRCS, 2006).

4.1. Life cycle of Yellow Starthistle

YST is a winter annual that germinates in the fall. Rosettes develop from the seedlings and appear in March–May. The plants bolt (produce erect stems) in May and June, sending up long stalks with spiny flowers. In summer bright yellow flowers appear. From late summer to early fall, the flower heads dry and release seeds, which are then dispersed by wind, water, human, and animal activity. The life cycle is completed when the plants die in the early fall. Flower heads disintegrate in winter, releasing a second type of seed (Thomsen et al., 1996; Sheley et al., 1999; Wilson et al., 2003).

YST is problematic in pastures. Even though the weed is edible for cattle at the early stages of its life cycle, when the plant is in the rosette-stage, the yellow flowers of YST have long spines that make cattle avoid grazing near the plant, thus increasing cattle management costs. Cattle that are forced to feed on this plant can incur injury (Sheley et al., 1999). In addition, YST infested pastures have less crude protein and digestible nutrients than uninfested pastures (Barry, 1995, as reported in DiTomaso). The annual economic impacts for livestock and forage crops have been estimated to run into the millions of dollars (Roché and Roché, 1991).

4.2. Yellow Starthistle control

While prevention is best (Griffith, 1999), this is not an option once land has been infested and is often not the option chosen by economic agents. Depending on the time of year a rancher can undertake various weed removal activities[3] including mowing, hand-pulling, fire, biological control, and herbicide treatments. Successful removal of the weed often requires the use of a combination of these activities. Mowing can be effective in managing stands of YST if done during the early flowering stages and then repeated about four weeks later. However, poor timing of mowing can actually decrease the competitiveness of other plants and aid in the spread of seeds (Thomsen et al., 1996). Mechanical control includes hand-pulling on a small scale. While hand-pulling removes the canopy of the plant and as much of the root system as possible, much of the root system will remain without tillage. Ten percent of YST seeds remain dormant for more than 10 years in the soil (Callihan et al., 1993; Griffith, 1999). Grazing sheep, cattle, and goats on YST after plants have bolted but before they have developed spines can help prevent the spread of seeds. Biological controls, such as the hairy weevil and the false peacock fly, can also be used (DiTomaso, 2006). The most frequently used method of control is chemical, i.e. herbicides. Herbicides have to be applied repeatedly over several seasons to remove an infestation. For simplicity, we focus on herbicide treatments in this application. We specify a weed removal function measuring percent weeds removed per acre, $r(e_{it})$ (%/ac), as:

$$r(e_{it}) = v_1 e_{it} - v_2 e_{it}^2, \tag{7}$$

where e_{it} is effort measured in terms of number of herbicide treatments per time period. This removal function assumes diminishing returns to effort and this is modeled via v_1 (%/ac/treatment) and v_2 (%/ac/treatment^2).

4.3. Competition between Yellow Starthistle and grass

The competitive success of YST is directly related to its rapid growth and resource capture (Sheley et al., 1993; Sheley and Larson, 1994). In addition, YST can alter soil microbiology and chemistry to its favor, increasing its own competitiveness and spread. However, these plant–soil feedback effects are small compared to the effects of dispersal and intrinsic growth (Levine et al., 2006). In addition, the species produces a large number of seeds with a high germination rate. Each adult YST plant produces between 20 and 120 seeds per plant depending on precipitation and density of stand (Sheley and Larson, 1994), but may produce up to 150,000 seeds. Of these, 95% are viable and in monocultures on observes about 2500 seedling plants per square foot. The seeds germinate as quickly as within 16 h of landing in soil with favorable conditions. Frost often will reduce the population of seedlings by 40%. As rosettes are developed, 60–75% die due to moisture stress or self-thinning. The maximum number of plants is generally 70 per square foot.

When competing with cheatgrass, YST has been found in experiments to have cycling population equilibria (Sheley and Larson, 1994). The Lotka–Volterra model is a system of non-linear differential or difference equations frequently used to describe competition between species that have cycling equilibria (Begon et al., 1990). In literature it is most frequently formulated for the case of two interacting species in which case the model reduces to two differential or difference equations. The equation for each competing species are essentially logistic models with a term added that accounts for inter-specific[4] competition (e.g. Brauer and Castillo-Chavez, 2000). As a result the Lotka–Volterra model can account for both intra- and inter-specific competition. The continuous time version of the differential system does not have an analytic solution (although it can be solved in the form of a difference equation (see e.g. Pistorius and Utterback, 1996)). However, in a simple model without management, it is possible to solve for the level of one species in terms of the other. Because of non-existence of an analytical solution for the continuous model, we have chosen to formulate the model in discrete time. The behavior of the discrete time model can be analyzed using numerical methods such as simulations, graphical analysis, and investigation of equilibria and their stability.

The basic Lotkta–Volterra model for weeds and grasses on agent i's plot of land, in the absence of management and grazing is formulated below. Grass g_{it} (lbs/ac/t), in absence of cattle grazing, grow according to

$$g_{it+1} - g_{it} = G(g_{it} w_{it}) = \gamma g_{it}\left(1 - \frac{(g_{it} + \alpha_{gw} w_{it})}{K_{gi}}\right), \tag{8}$$

where γ (1/t) is intrinsic growth rate of grass and K_{gi} (lbs/ac/t) is the carrying capacity of grass on agent i's plot of land. Growth of grasses is adjusted for competition with the weed through the $\alpha_{gw} w_{it}$ (lbs/ac) term, which transforms weeds into "grass-equivalents." The growth of the invasive weed w_{it} (lbs/ac) on agent i's plot of land

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[3] Tillage is usually not appropriate in rangelands because of potential damage to other desirable species, erosion, and the possibility of re-infestation if subsequent rainfall (DiTomaso and Gerlach, 2000).

[4] Interspecific means "between two or more species" (Lincoln et al., 1998).

is given by

$$w_{it-1} - w_{it} = W(g_{it}, w_{it}) = \omega w_{it}\left(1 - \frac{(w_{it} + \alpha_{wg} g_{it})}{K_{wi}}\right), \tag{9}$$

where ω (1/t) is the intrinsic growth rate of weeds and K_{wi} (lbs/ac/t) is the carrying capacity of weeds on agent *i*'s plot of land. Analogous to the growth model for grasses, the coefficient α_{wg} measures the competitive effect on weeds by grass.

When both competition coefficients (α's) are positive the two species are competing. If the competition coefficient takes a value[5] $\alpha > 1$ the competitive effect of weeds on grasses is greater than the competitive effect of grasses on its own members. If $0 < \alpha \leqslant 1$ the competitive effect of weeds on grasses is less than the competitive effect of grasses on grasses. If $\alpha = 0$ then the first right-hand side term of the growth model for grass reduces to a single species logistic model with no interspecific competition. The basic Lotka–Volterra model, in Eqs. (8) and (9), has four possible equilibria: both species go extinct, only one of the species goes extinct, or the species co-exist.

4.4. Seed dispersal

Human activities, such as vehicle travel and the movement of hay, seed, gravel, and soil, are the primary cause of long-distance movement of YST (DiTomaso, 2006; Roché and Thill, 2001). Once at a new location, animals and humans move seeds over short to medium distances (DiTomaso, 2006). Many advanced seed dispersal models exist (see e.g. Levin et al., 2003). Our model focuses on short-distance diffusion because this isolates the effects of decision making between agent *i* and *j*. YST is also characterized as having a slow invasion front. Roché and Roché (1991) found that 92% of seeds fell within two feet of the parent plant and that the maximum dispersal distance was only 16 feet. We therefore set $\bar{w}_t = 0$ in the diffusion function. Future work could incorporate theoretical expectations to the change in diffusion as a result of strategic behavior between agent *i* and *j*. Without such adjustment for strategic behavior the diffusion function will simply relate weed levels on agent *j*'s pasture to weed levels on agent *i*'s plot of land is therefore specified as

$$d(w_{jt}) = d_1 w_{jt}, \tag{10}$$

where d_1 is per lbs/ac of weed increase in dispersal from agent *j*'s land to agent *i*'s land caused by greater weed infestation levels on agent *j*'s parcel of land. Here weed-level on agent *j*'s land w_{jt} determined by the specific effort level chosen by agent *j*. Notice that because plants are stationary the diffusion is always non-negative; with animals net diffusion can be either negative or positive.

4.5. Cattle feeding and growth

Following Huffaker and Wilen (1991), we define a "Michaelis–Menten" function to model the grass feeding behavior of the stock of cattle placed on the pasture s_{i0}:

$$f(g_{it}) = \frac{q_m g_{it}}{g_{it} + q_h}, \tag{11}$$

here q_m is the maximum (satiation) daily consumption per acre for the stock of cattle (lbs/ac), i.e., $q_m = ms_{i0}$, with m being the percent weight gain per unit of grass consumed, and q_h, the "Michaelis constant" measures the forage level at which the stock of cattle (lbs/ac) is half-satiated each day and we assume that $q_h = 0.5ms_{i0}$. The growth of cattle placed on pasture is modeled as a percentage of the feed intake by the cattle. That is:

$$s_{it} = s(g_{it}) = mf(g_{it}). \tag{12}$$

4.6. Net benefits

We assume that the production function is separable so that we can model the cattle and weed infestation problem separately from other operations on the ranch. A simplifying assumption is that in each time period any growth of the stock of cattle is immediately sold. The net benefit function for agent *i* is total revenue from selling off the weight gain of the stock of cattle minus the costs of weed removal efforts and the marginal cost of growing the cattle stock, which is specified by

$$V_{it} = ps(g_{it}) - c(s_{it}, e_{it}), \tag{13}$$

where p (\$/lbs) is the price per pound of beef sold, $s(g_{it}) = mf(g_{it})$, and $c(s_{it}, e_{it})$ (\$/t) is the cost of growing and maintaining the current stock of the animals, $s_{it} = s(g_{it})$ (lbs/ac), and spending e_{it} dollars on effort to combat the weed. The cost function is defined as $c(s_{it}, e_{it}) = c_s s_{it} + c_e e_{it}$ where c_s is the cost (\$/lbs/ac) cattle production and c_e (\$/treatment/ac) cost of herbicide applications.

In the following optimizations, agent *j*'s pasture is considered a source of weeds for agent *i*. The model for agent *j* does not include any particular production for agent *j* since agent *j* could be any one of several types of producer or land that is not in production at all. The following section develops and evaluates various simulation scenarios.

5. Dynamic simulation scenarios

Based on the model presented in the previous section for YST, this section provides simulation results for the two hypothetical agents, *i* and *j*. The results include the optimal effort level for agent *i* under several scenarios of initial weed levels and effort levels for agent *j*.

The simulation scenarios may be conceptualized as follows. Agent *i*, a beef producer, observes agent *j*'s efforts and level of YST infestation and chooses her optimal effort

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[5] Subscripts "gw" and "wg" are here dropped for simplicity.

level, in order to maximize net benefits. Agent i problem is described by Eqs. (4a)–(4d) with functional forms given in Eqs. (7)–(12). This agent's objective is to choose the optimal effort level given the observed actions of agent j and the initial rangeland conditions. Agent i is a price taker with a zero discount rate. Agent j's effort level and initial weed infestation level are chosen for each simulation. For simplicity, growth and competition of grass and YST on agent j's pasture follow the basic Lotka–Volterra model [Eqs. (8) and (9)] adjusted for weed removal [Eq. (7)] as follows:

$$g_{jt+1} - g_{jt} = G(g_{jt}w_{jt}), \tag{14a}$$

$$w_{jt+1} - w_{jt} = W(g_{jt}, w_{jt}) - r(e_{jt})w_{jt}, \tag{14b}$$

$$g_j(t=0) = g_{j0}w_j(t=0) = w_{j0}. \tag{14c}$$

Using this joint model specified for agents i and j and parameter values[6] given in Table 1, we run a base set of simulations to identify optimized effort level, e_{it}, for agent i for the case of no governmental intervention. The simulations are run for a 5-year period because of the cycling characteristic of the Lotka–Volterra model and because we assume that ranchers frequently update their weed management policy. We employ POWERSIM$^{\text{TM}}$, a dynamic simulation platform, to find an open-loop, efficient effort level[7] for agent i.

For each agent, we assume to possible initial YST infestation levels: H and L, correspond to 30% and 1% of total weed carrying capacity, respectively. In addition, we assume two possible effort levels for agent j: 0 and 1, where 0 indicates no herbicide treatments in a year and 1 indicates one herbicide treatment pre year. Given these initial pasture conditions and effort levels for agent j, there are eight base case simulations. Each simulation is coded by, first, the initial infestation level on agent i's land (H or L), second on agent j's land (H or L), and agent j's effort (0 or 1), e.g. LL0. Table 2 presents the base-case outcomes for agent i including the optimal number of treatments annually and cumulative net benefits. The simulations indicate that regardless of the beginning levels of infestations and regardless of the effort level by agent j, it is never optimal for agent i to exert any effort to mitigate weed infestations. This somewhat surprising result is consistent with Hartmans et al. (1997) who find that herbicide treatments of YST are cost prohibitive to cattle productions. This result is also, anecdotally consistent with responses from New Mexico ranchers who participated in focus groups during 2006.

While the optimal choice of agent i is consistent in the base cases the impact of the "do-nothing" approach depends on initial pasture conditions. Figs. 1 and 2 present two of the eight grass and weed profiles for agents i and j. Fig. 1 depicts the results from the LL0 scenario which is the first scenario in Table 2. In this case, the initial weed levels are low and neither agent exerts effort. While grass and YST co-exist in the absence of grazing pressure on agent j's land, grazing pressure eventually leads to the collapse of the stock of grass on agent i's land. This result is consistent with Hobbs and Humphries (1995) who cite environmental changes such as grazing as one of the triggers for the rapid spread of weed. Furthermore, in this initial scenario, the competition from grass is enough to retard the spread of YST on j's land except in the case where the initial infestation level on agent j's land is high. Fig. 2 presents the results from the LH0 scenario. In this case, not only does the grass stock on agent i's land collapse more rapidly, YST increases more rapidly. These two results are direct consequences of contribution of weed from agent j's pasture to agent i's pasture via YST diffusion. Comparing agent i's outcomes, the case with the higher level of initial weed infestation has a faster build-up of the weed stock with YST becoming the dominant species. Outcomes for agent j are generally a lower level of grass through the 5 years and a more rapid increase in the weed stock.

The above results suggest that, at least in the case of YST under the conditions modeled, the potential for private, proactive management of the invasive species may be nonexistent. This begs the question, for what economic (and biologic) parameters would it be optimal for agent i to exert effort in order to mitigate the spread of the weed? Specifically, how large an incentive would be required in order to have agent i choose mitigation?

In order to answer this, we use sensitivity analysis to find the minimum cost sharing or financial incentive necessary for mitigation to have a strictly positive impact on agent i's outcome. After finding the minimum required incentive, we find the optimal effort level for agent i. The incentive is modeled as a percentage of the costs of mitigation. The results presented, do not consider the total societal or public impacts of such a cost-sharing scheme such as reduced spill-over effect of weeds, market distortion and environmental effects. In addition, future benefits resulting from reduced weed infestation levels after the 5 year run of the model will clearly not be accounted for. We consider the same infestation levels (H and L) and agent j effort levels (0,1) as in the base case. Table 3 presents the simulation results with an "I" appended to the scenario code to indicate "incentive scenario".

The results show that the response to the incentive changes dramatically with the type of weed-effort scenario. In the LL0I simulation an incentive of about 50% of the effort cost is necessary in order to make agent i exert any weed removal effort. With this incentive, the agent will choose to apply the treatment of approximately 1.5 times per year, which increases her cumulative profits by less

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[6] Model simulations showed that herbicide treatments are not profitable for cattle farmers in general in New Mexico which is consistent with the literature. We chose to focus on the higher productivity land in northern New Mexico profitability of such treatments are more likely.

[7] POWERSIM employs the Newton Raphson algorithm for this optimization process.

Table 1
Symbol definitions and values

Symbol	Definition	Unit	Value
e_{jt}	Weed removal effort in terms of herbicide treatments for agent j	trt/ac/day trt/ac/yr	0.0027 1
K_g	Carrying capacity of grasses[a]	lbs/ac	3000
K_w	Carrying capacity of weeds[b]	lbs/ac	2500
g_{i0}-g_{j0}	Initial level of biomass of grass	lbs/ac	1000
w_{i0}, w_{j0}	Initial level weed infestation for agents i and j	lbs/ac	$L = 1\%$ of K_w $H = 30\%$ of K_w
s_c	Carrying capacity for cattle on pasture[c]	lbs/ac	480
γ	Intrinsic growth rate grass[d]	1/day	0.042
ω	Intrinsic growth rate weed[e]	1/day	0.005
α_{gw}	Per capita effect on grass by weed[f]	–	1.2
α_{wg}	Per capita effect on weed by grass[g]	–	0.2
m	Forage conversion factor	1/day	0.03
q_m	Maximum daily consumption per animal unit	lbs/day	30
q_h	The consumption level of grass where an animal unit is half satiated	lbs/day	15
v_1	Weed removal efficiency parameter[h]	%/ac/trt	0.3518
v_2	Weed removal efficiency parameter	%/ac/trt^2	0.0215
d_i	Seed dispersal rate[i]	%/day	0.00027
p	Price per pound of beef cattle in New Mexico[j]	\$/lb	1.1503
c_s	Average production cost per pound of beef cattle in Northern New Mexico[k]	\$/lb	1.00
c_e	Marginal cost of herbicide treatment	\$/trt	6.30
A	The average acreage of agent i's a New Mexican ranch[l]	ac	1
δ	Interest rate[m]	–	0

[a] Griffith (1999).

[b] The carrying capacity for weeds is calculated as $K_w = K_g/\alpha_{gw}$.

[c] http://www.gao.gov/new.items/d05869.pdf last accessed 10/30/06 ratio of animal units to BLM rangeland in New Mexico. 0.16 BLM estimate of AU/ac for BLM land.

[d] Noy-Meir (1976) reports 0.084 for highly productive land. Because of low precipitation in New Mexico we use 0.042, i.e. 50% of this estimate.

[e] http://www.farmfoundation.org/projects/documents/Tschirhart.pdf, last accessed 10/27/06. Bureau of Land Management estimate the weed growth rate to be 14%/month which corresponds to ≈0.005%/day

[f] We assume that one weed plant corresponds to 1.2 grass plants.

[g] We assume that one grass plant corresponds to 0.2 weed plants.

[h] We determined v_1 and v_2 by assuming that 1 treatment removes 80% of the weed, 2 treatments removes 95% of the weed and 3 treatments removes 99% of the weed. A non-linear curve connecting these points have the coefficients $v_1 = 0.3518$ and $v_2 = 0.0215$.

[i] This corresponds to a yearly rate of 10%.

[j] New Mexico Combined Weighted Average Feeder Cattle Report from the USDA Department of Agriculture News website http://www.ams.usda.gov/lsmnpubs/Live.htm, last accessed 11/05/06.

[k] http://costsandreturns.nmsu.edu/2006%20Ranch.htm, last accessed 11/05/06.

[l] The model is formulated on a "per/acre" basis.

[m] Since price and costs are not adjusted over time we have set the percent interest rate to zero.

Table 2
Base case simulations

Simulation scenario	Optimal number of annual treatments for agent i	5-year total net benefits (\$ per acre)
LL0	0	47.46
LL1	0	48.29
LH0	0	31.08
LH1	0	32.53
HL0	0	3.79
HL1	0	3.79
HH0	0	3.61
HH1	0	3.62

than one dollar from the base case. This increase in net benefits would not offset the cost of the incentive over the time period, which would be approximately \$24.10.

In the cases where both agents have high weed infestation, a higher percentage incentive, 75%, is necessary for agent i to participate. In these cases, the optimal number of treatments is over five (approximately one during each growing month). Similarly, in the cases where only one agent has high initial weed levels, we found that the percentage incentive needed to be 63% with effort levels ranging from about 3.5 to 4.5 per year. While the incentive levels may appear high, they are consistent with those provided in a northern Idaho cost-sharing program where the cost-sharing percentage for YST ranged from 50% to 70% (Hartmans et al., 1997).

The impacts on net benefits are fairly large. The impact on net benefits for the HH0 scenarios is an increase of \$29.82, while for the HH1 scenario, the impact is a \$31.90 increase in net benefits. It should be noted that in all of these cases, the increase in the profits of the agent are less

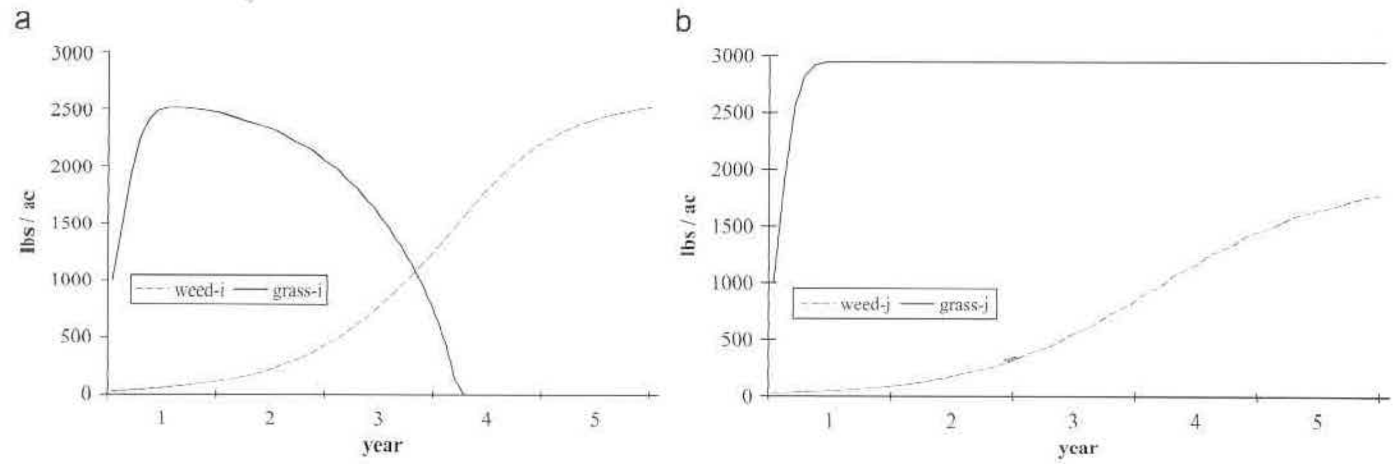

Fig. 1. Scenario LL0 from Table 2: panel (a) the results for agent *i*, and (b) the result agent *j*.

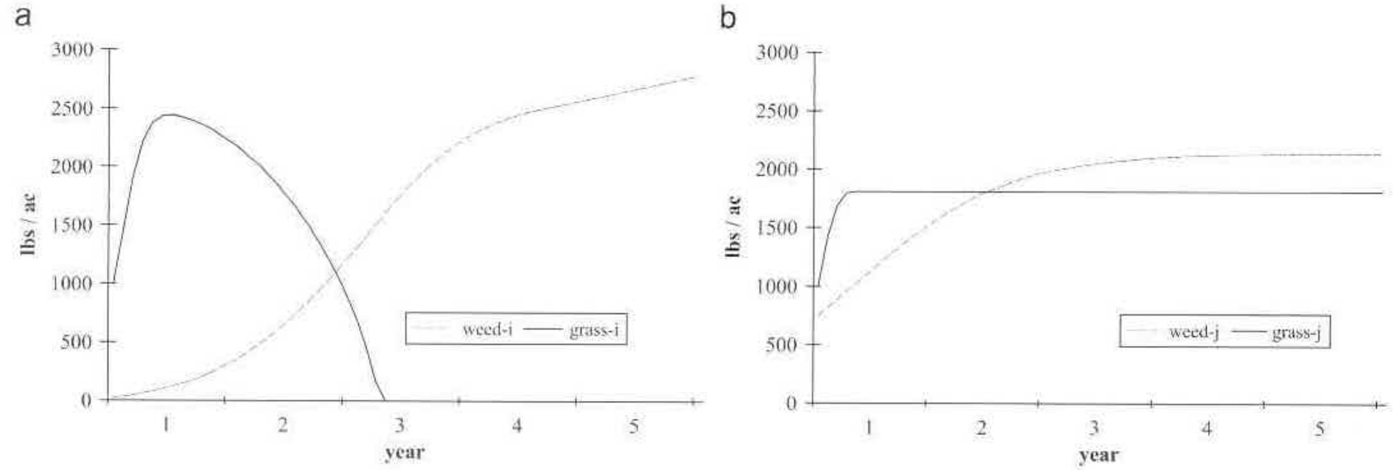

Fig. 2. Scenario LH0 from Table 2: panel (a) the results for agent *i*, and (b) the result agent *j*.

Table 3
Incentive results for agent *i*

Simulation scenario	Incentive[a] (percent of effort costs)	*Optimal treatments per year*	Cumulative 5-year net benefits ($)	Total subsidy over 5 years to agent *i* $
LL0I	50%	1.53	48.43	24.10
LL1I	50%	1.84	52.39	28.98
LH0I	63%	3.53	34.16	70.05
LH1I	63%	3.31	38.58	65.70
HL0I	63%	4.56	23.45	90.52
HL1I	63%	4.52	25.15	89.72
HH0I	75%	5.49	33.43	129.84
HH1I	75%	5.37	35.52	127.00

[a] Cost sharing levels are derived as follows: we use sensitivity analysis to find the minimum cost sharing or financial incentive necessary for mitigation to have a strictly positive impact on agent *i*'s outcome. After finding the minimum required incentive, we find the optimal effort level for agent *i*. The incentive is then modeled as a percentage of the costs of mitigation.

than the level of the incentive payment. The cumulative costs of the incentive payment in these two cases were $129.84 and $127, respectively. Notice that the cost of the incentive payment was reduced when agent *j* also exerted weed removal effort.

In the majority of simulations in Table 3 (LH0I, LH1I, HL0I, HL1I, HH0I, and HH1I) agent *i* exerts less effort when agent *j* treats than when agent *j* does not treat. This is consistent with the freeriding strategy discussed in Section 3 [i.e., where $\partial e_i^*/\partial e_j < 0$ in Eq. (6a)] where agent *i* could choose to freeride on agent *j*'s efforts to remove weed. Additionally, agent *i* receives greater net benefits when agent *j* treats. Scenarios, LL0I and LL1I found that agent *i* optimally should spend more money on treatments when agent *j* is treating, indicating that if both agents have low initial weed levels collaborative weed removal strategies may be possible.

The impact of the cost-sharing incentive-program on pasture conditions on agent *i* and *j*'s land are presented in Figs. 3–10. Fig. 3 presents the LL0I simulation results. Comparing outcomes for agent *i*, in Figs. 1a and 3a, the impact of effort is clearly seen. The stock of grass on agent *i*'s land does not collapse in presence of the incentive (3a) within the 5 year time span, as it does in the base case (1a). However, the weed removal efforts are not sufficient to keep the growth of the weed under control. The land suffers a slower decline of the grass stock and a slower approach to a state of weed dominance. While the 5-year short-run impact is slightly positive for agent *i*, it appears that the incentive may simply prolong the inevitable, which is that the land becomes less and less productive as the weeds become more established. Figs. 1b and 3b do not change since in both cases agent *j* does not exert effort and diffusion from agent *i* to agent *j*'s land is not modeled.

Figs. 3a–10a, show that as effort increases the grass stock as expected improves it chances against the weed. In Figs. 3a–7a, (LL0I, LL1I, LH0I, LH1I, and HL0I) the curves for stock levels for the weed and the grass eventually cross and the weed becomes dominant in the pasture. Fig. 8a (scenario HL1I) shows that when agent *j* also exerts effort, grass and not weed becomes dominant in the field. However, since agent *j* is limited to one treatment, the stock of the weed on agent *j*'s pasture increases and start diffusing back to agent *i*'s pasture so that the weed stock actually increases a little toward the end of the 5 year period. The two last figures show that when cost sharing is as much as 75%, the weed become near eradicated in scenario HH0I (Fig. 9a) and eradicated in scenario HH01 (Fig. 10a). For agent *j*, who does not use her pasture for grazing, the simulation scenarios show that the weed only becomes dominant in the case where there is high initial level of infestation and there is no effort level. Even if the

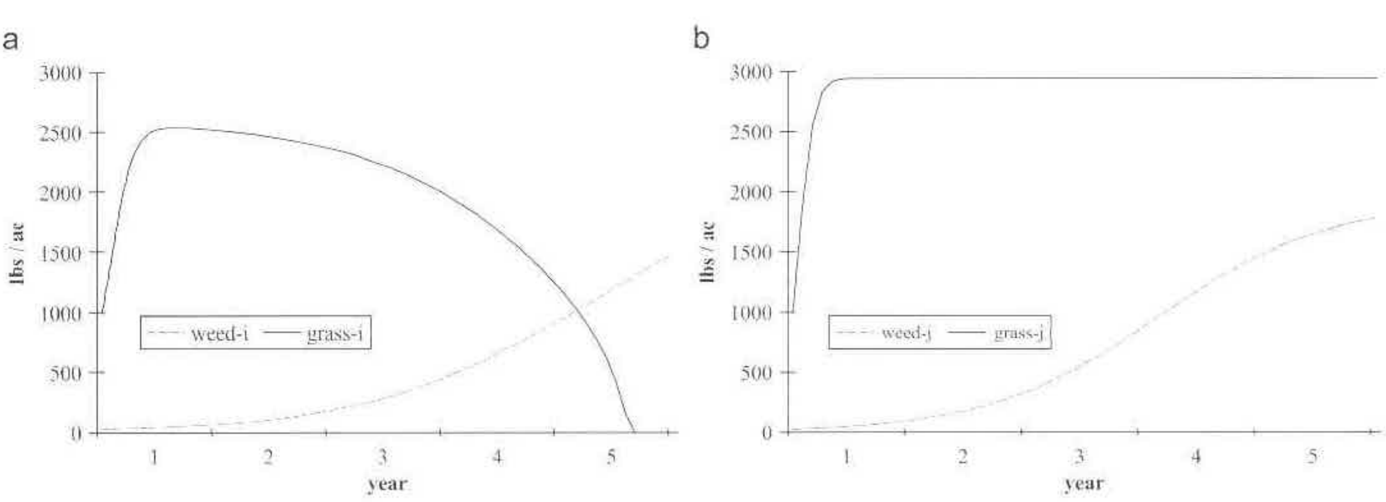

Fig. 3. Scenario LL0I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

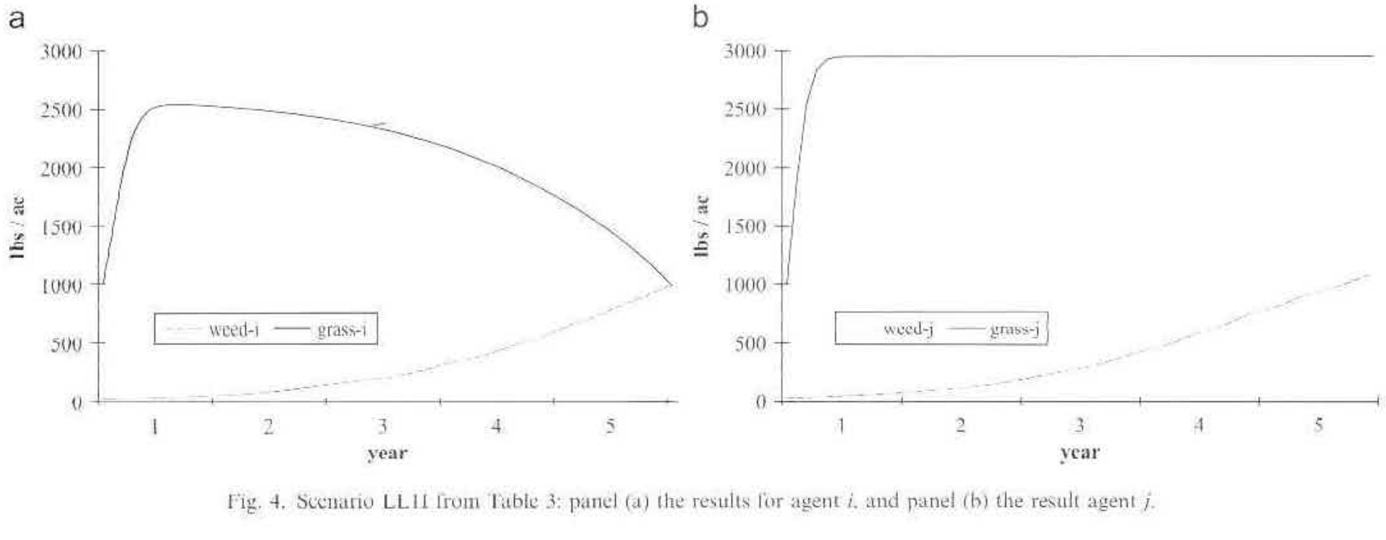

Fig. 4. Scenario LL1I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

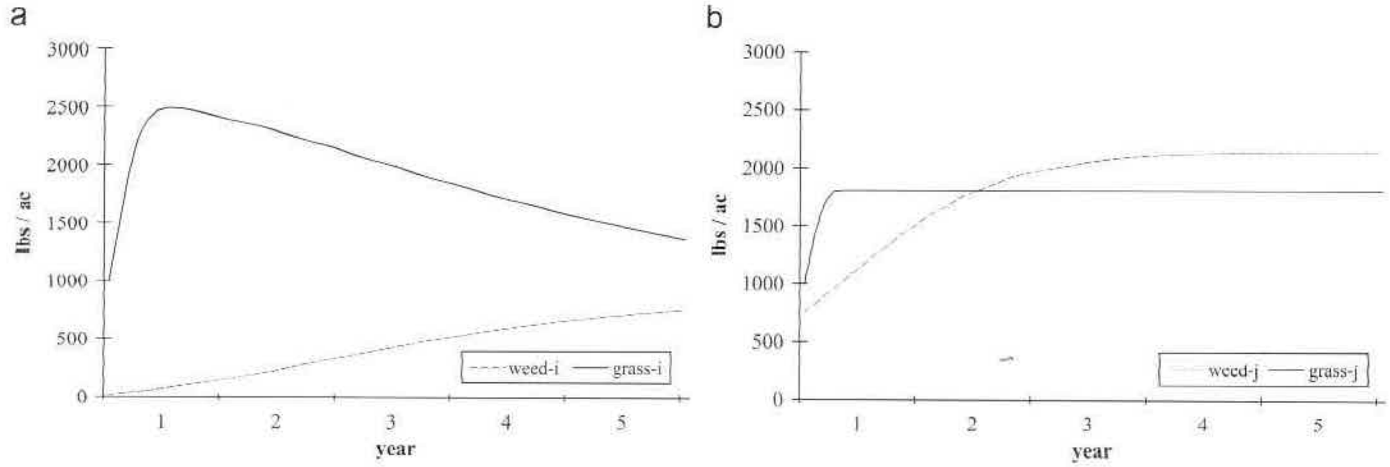

Fig. 5. Scenario LH0I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

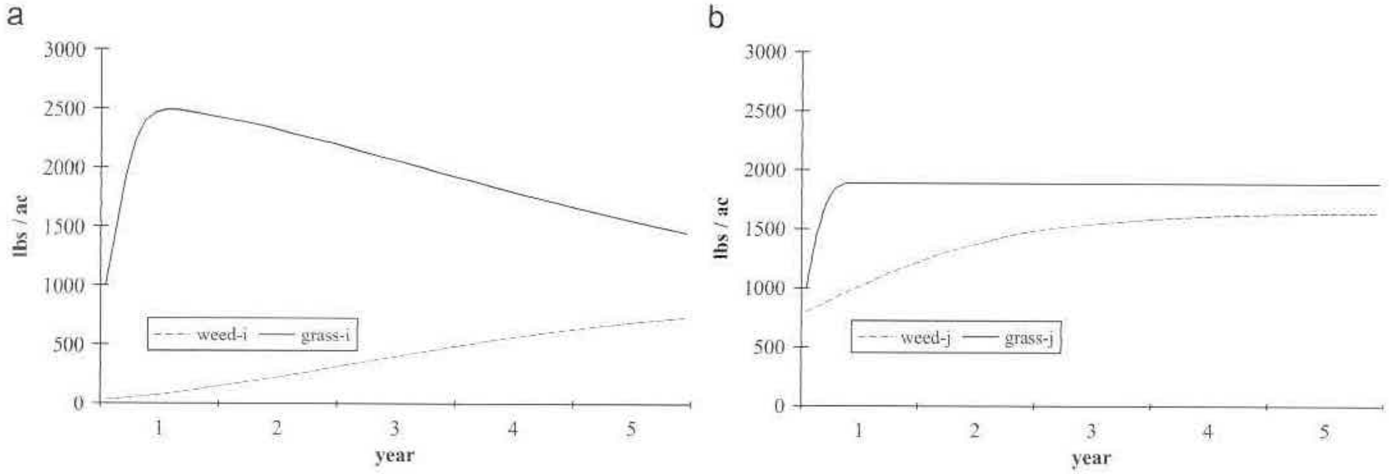

Fig. 6. Scenario LH1I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

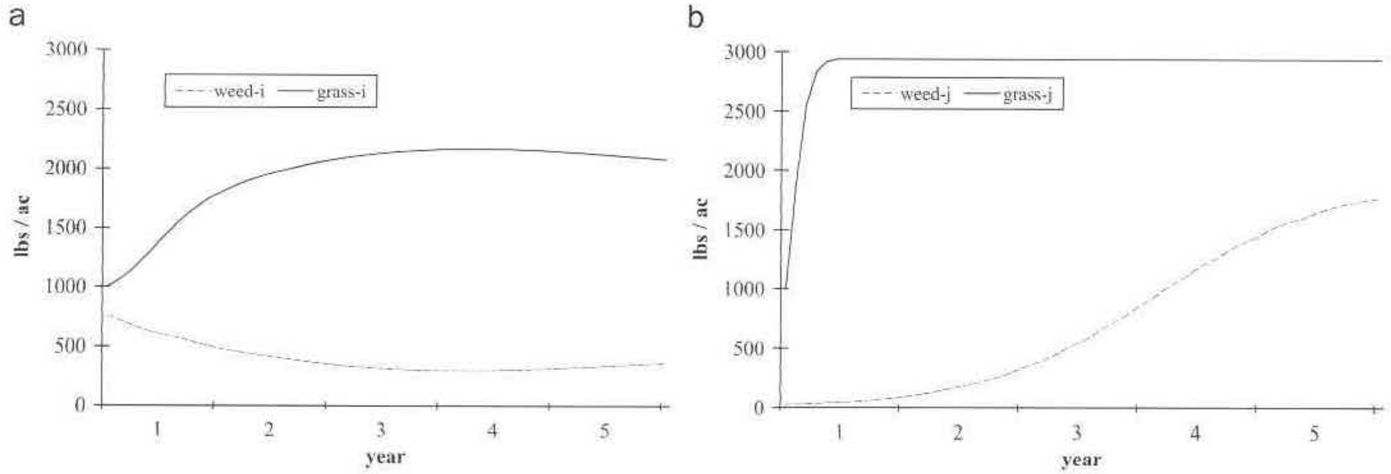

Fig. 7. Scenario HL0I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

weed is not more abundant in terms of biomass than the grass in the other scenarios the weed is still quite abundant and would represent a problem for future users of the pasture. The results for agent *j* are mostly interesting for investigating the very strong effect grazing has on reducing the competitiveness of the grass in the presence of the weed

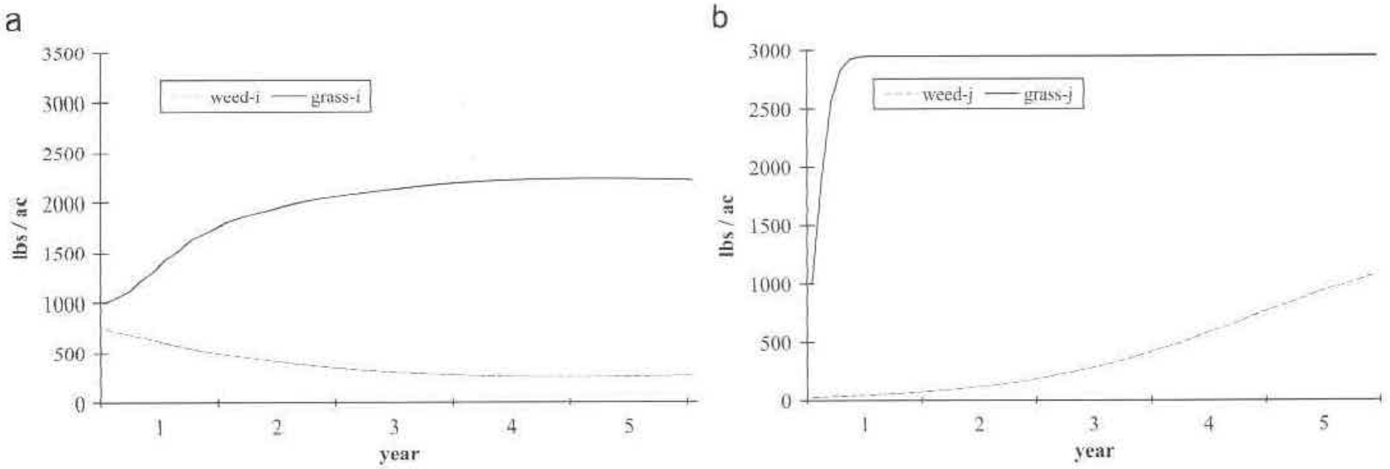

Fig. 8. Scenario HL1I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

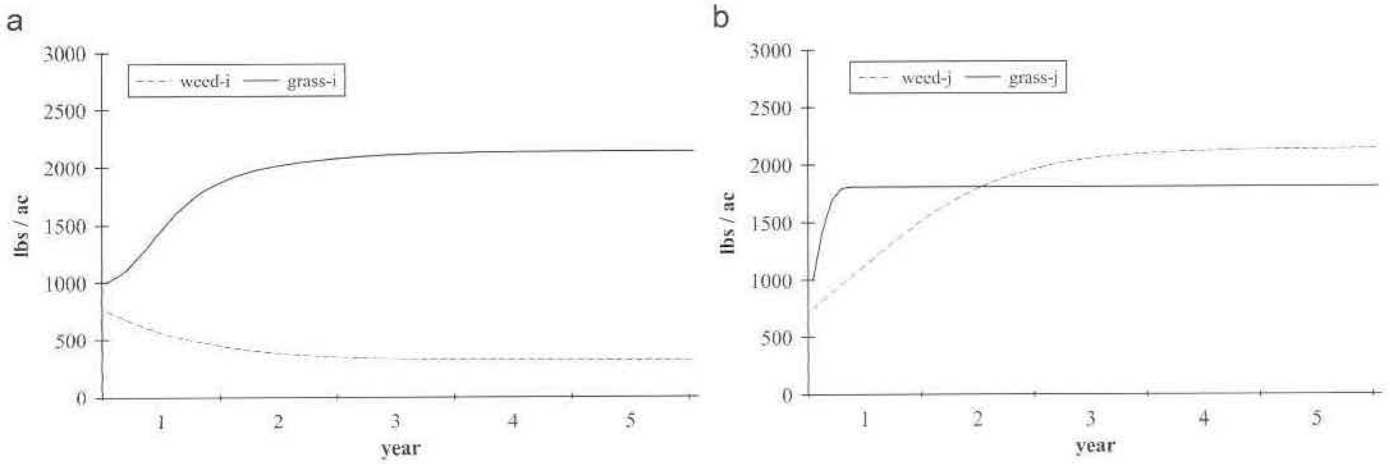

Fig. 9. Scenario HH0I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

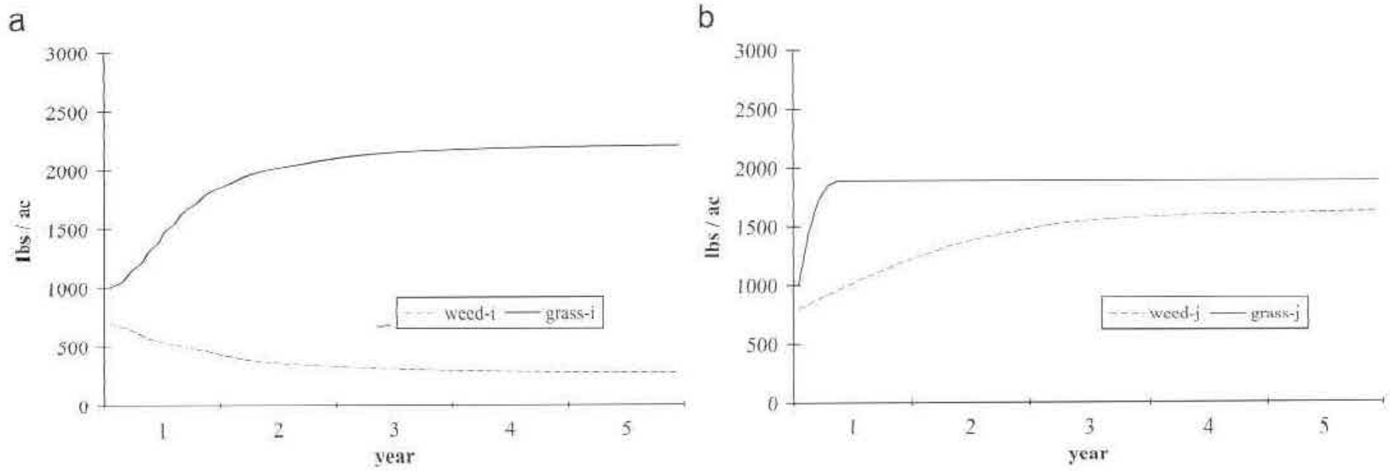

Fig. 10. Scenario HH1I from Table 3: panel (a) the results for agent *i*, and panel (b) the result agent *j*.

and ultimately shifting the species composition on the pasture.

Finally, it may seem counterintuitive that the weed control is better when initial weed infestation levels are high (compare e.g. Fig. 3 with Fig. 10). This is a direct result of the increased number of treatments that become affordable when the level of cost-sharing increases. When re-running simulation LL0I with a 75% cost-sharing instead of a 50% cost-sharing, optimal effort levels increases to 2.65 (as compared with 1.53 originally) which and cumulative cost of the cost-sharing program is $62. This is only half of the cumulative costs of starting cost-sharing at a point when weed levels are high. This indicates that costs of weed control can be reduced by attacking the problem at an early stage.

6. Conclusion and future work

It is reasonable to assume that in order to minimize the impact of an invasive weed; the best strategy would be to expend high effort levels as soon as the weed appears. It may also be the only way to eradicate the weed in the long run if that is a goal. While some degree of invasive weed control generally is considered desirable for both private ranchers and the public, weed control costs can be quite high for private ranchers and in some cases too high. Trading-off these costs against other more immediate costs, such as energy costs, may make it difficult for any type of voluntary invasive weed control program to work. When weighing costs and benefits it must be recognized that efforts expanded to combat weeds on one rancher's plot of land benefits the whole community since it contributes to limit weed diffusion. As stated by Eisewerth et al.: "YST control has both a private and a public good component" implying that "…, public expenditures on YST control are warranted" (Eisewerth et al., 2005, p. 2).

Based on the bioeconomic model presented in this paper, we find that without some form of incentive payment the rancher will not exert any effort to control YST. We also find that unless the cost-sharing is sufficient to cover the costs of several treatments, eradication/control is difficult. Not unexpectedly, we find that neither efficient control nor eradication is possible unless control efforts are exerted by both agents simultaneously. In other words, coordinated efforts are required to minimize impact. Another result found from our simulations is that coordinated efforts between agents are more likely while infestation levels are low. Policies designed for early intervention with flexibility to fit different weeds and scenarios may prove most difficult to design, but most effective. The design of such policies, however, is well beyond the scope of this paper.

Interesting future extensions of this initial and simpler model include investigating the functional forms of reaction functions and their feedback effects, as well as attempting to solve both agents' optimization problem jointly where agent *j* is either modeled as some type of a private producer or a public entity. Other possible extensions include modeling the diffusion function using developments in mathematical biology.

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A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa

B.W. van Wilgen[a,*], B. Reyers[a], D.C. Le Maitre[a], D.M. Richardson[b], L. Schonegevel[a]

[a] *Centre for Invasion Biology, CSIR Natural Resources and the Environment, P.O. Box 320, Stellenbosch 7599, South Africa*
[b] *Department of Botany and Zoology, Centre for Invasion Biology, University of Stellenbosch, Private Bag X1, Matieland 7602, South Africa*

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Abstract

This paper reports an assessment of the current and potential impacts of invasive alien plants on selected ecosystem services in South Africa. We used data on the current and potential future distribution of 56 invasive alien plant species to estimate their impact on four services (surface water runoff, groundwater recharge, livestock production and biodiversity) in five terrestrial biomes. The estimated reductions in surface water runoff as a result of current invasions were $>3000\,\text{million}\,m^3$ (about 7% of the national total), most of which is from the fynbos (shrubland) and grassland biomes; the potential reductions would be more than eight times greater if invasive alien plants were to occupy the full extent of their potential range. Impacts on groundwater recharge would be less severe, potentially amounting to approximately 1.5% of the estimated maximum reductions in surface water runoff. Reductions in grazing capacity as a result of current levels of invasion amounted to just over 1% of the potential number of livestock that could be supported. However, future impacts could increase to 71%. A 'biodiversity intactness index' (the remaining proportion of pre-modern populations) ranged from 89% to 71% for the five biomes. With the exception of the fynbos biome, current invasions have almost no impact on biodiversity intactness. Under future levels of invasion, however, these intactness values decrease to around 30% for the savanna, fynbos and grassland biomes, but to even lower values (13% and 4%) for the two karoo biomes. Thus, while the current impacts of invasive alien plants are relatively low (with the exception of those on surface water runoff), the future impacts could be very high. While the errors in these estimates are likely to be substantial, the predicted impacts are sufficiently large to suggest that there is serious cause for concern.

Keywords: Biodiversity; Fynbos; Grassland; Grazing; Groundwater; Hydrology; Karoo; Savanna; Water yield

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1. Introduction

Ecosystems deliver a wide range of services to humanity (e.g. Daily, 1997; Constanza et al., 1997). A 4-year global assessment of the world's ecosystem services (Millennium Ecosystem Assessment, 2005), found that 60% of the services assessed were declining in condition due to a suite of anthropogenic drivers (such as habitat loss and alteration, water abstraction, overexploitation, and invasive alien species). The invasion of ecosystems by alien species has been identified as a large and growing threat to the delivery of ecosystem services (Drake et al., 1989). Invasive alien species are a product of the ongoing and increasing human re-distribution of species to support agriculture, forestry, mariculture, horticulture and recreation, as well as a result of accidental introductions. They include disease organisms, agricultural weeds, and insect pests. These species are known to erode natural capital, compromise ecosystem stability, and threaten economic productivity. The problem is growing in severity and geographic extent as global trade and travel accelerate, and as human-mediated disturbance, global changes in climate and biogeochemical cycling, and increased dissemination of propagules makes ecosystems more susceptible to invasion by alien species (Le Maitre et al., 2004). Besides their impacts on agriculture, forestry and human health, biological invasions are also widely recognised as the

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*Corresponding author. Tel.: +27 21 888 2400; fax: +27 21 888 2693.
E-mail address: bvwilgen@csir.co.za (B.W. van Wilgen).

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second-largest global threat (after direct habitat destruction) to biodiversity (Mooney and Hobbs, 2000; Secretariat on the Convention on Biological Diversity, 2001).

Ecosystem services can be grouped into those that meet basic human needs (supporting, regulating, and provisioning services) and those that enhance human well-being (cultural services). Supporting services underpin the basic life-support processes required to sustain all ecosystems, while regulating services control the flow of benefits and treatment of wastes, pests, and diseases. Provisioning services provide products for human use, and cultural services enhance the quality of human life and human well-being. Human well-being, although buffered to some extent against environmental vagaries by culture and technology, is ultimately determined by the continued supply of these services (Millennium Ecosystem Assessment, 2005). Services can be delivered by natural as well as highly managed ecosystems.

Biodiversity plays an important role in the delivery of ecosystem services. It can also be a service in its own right, for example, as the basis of nature-based tourism. In other cases, biodiversity is needed for ecosystems to function effectively, and thus to deliver services (de Groot et al., 2002). Although there is much debate as to which aspects (quantity, variability, distribution, or condition) of genes, species, and ecosystems are important for the continued delivery of ecosystem services, there is general agreement that overall biodiversity is important for ensuring the resilience of ecosystem functions and services (Loreau et al., 2001; Diaz et al., 2006). Ecosystems that retain their full complement of biodiversity are also more resistant to the biological invasions that erode ecosystem services (Diaz et al., 2006).

The impacts of invasive alien species on ecosystem services, and on biodiversity, are significant (estimates vary, but the total costs can be in the order of tens of billions of US$ each year, McNeely, 2001; Pimentel, 2002; Pimentel et al., 2005). Despite their apparent importance, few studies have sought to estimate the impact of invasive species on the delivery of ecosystem services at a broad-scale. The few studies that have been done have either focussed on a single ecosystem service (for example, on surface water supplies, Le Maitre et al., 2000), or on a single species (for example, the black wattle, De Wit et al., 2001). Broad-scale studies are urgently needed to support the estimation of economic impacts at a level appropriate to policy-makers. They are also needed to provide a basis for deciding on the proper levels of funding for control operations, and to identify priorities for management intervention.

In South Africa, considerable amounts are spent on the control of invasive alien plants. Over the past 10 years, government's contribution to control programmes amounted to over R3 billion (approximately US$500 million; Anonymous, 2004). A combination of the predicted effects of invasive alien plants on water resources, and the potential for clearing projects to generate much-needed employment, allowed government to justify this level of expenditure (van Wilgen et al., 2002). However, recent reviews have highlighted the need for better assessments of the problem. Richardson and van Wilgen (2004) concluded that the consequences of invasions for the delivery of ecosystem services are, with the notable exception of impacts on water resources, poorly studied. Another review (Görgens and van Wilgen, 2004) concluded that a good deal of knowledge existed regarding the effects of invasive plants on water resources. This study also showed, however, that there were large gaps in understanding, and challenging problems associated with scaling up the knowledge generated at one level to make predictions at a higher, more meaningful, level. In this paper, we report on a spatially explicit assessment of the current and potential impacts of invasive alien plants on selected ecosystem services and biodiversity in the major terrestrial biomes of South Africa (a biome is a large, regional ecological unit, usually defined by a dominant vegetative pattern). This was conducted to provide a preliminary estimate of the size and location of the impacts, to explore the feasibility of using existing information and data to make such assessments, and to identify areas where information needs to be improved. The assessment is the first attempt to quantify the impacts of more than one ecosystem service in a spatially explicit manner at a national scale in southern Africa.

2. Methods

2.1. Sources of data

We restricted our assessment of impacts to ecosystems within five major terrestrial biomes in South Africa. The biomes were the fynbos (mediterranean shrublands), grassland, savanna (including the thicket biome, *sensu* Vlok et al., 2003), Nama karoo (arid shrublands), and succulent karoo. A range of spatial datasets, captured in a geographic information system, were used to assess the possible impacts of invasions on ecosystem services from each of these biomes (Table 1). The extent of each biome, and the degree of transformation and protection, varies considerably between biomes (Table 2).

2.2. Selection of important invasive alien plant species

We developed two lists of invasive alien plant species for each biome (Table 3). The first lists the species that are currently of importance in each biome (the "current list"), and the second lists those that would become dominant in each biome if they were allowed to reach their full potential (the "future list"). We used the South African Plant Invaders Atlas (SAPIA) database (Henderson, 1998) to derive the current list. The SAPIA database contains records of alien plant species presence within quarter-degree squares (a grid of approximately 25 × 25 km^2). We placed all invasive alien plant species that occurred in

Table 1
Salient attributes of spatial datasets used to assess the impacts of invasive alien species on ecosystem services in South Africa

Dataset	Description	Scale	Use	Source
Terrestrial vegetation in South Africa, Lesotho and Swaziland	Map of 68 major vegetation types	1:250,000	Definition of boundaries of major biomes	Low and Rebelo (1996)
	Map of 441 major vegetation types	1: 250,000	Definition of groundwater-dependent ecosystems	Mucina and Rutherford (2004)
Landcover	Satellite-derived classification of land use	1: 250,000	Exclusion of ecosystem services not derived from transformed areas	Thompson (1996)
Protected areas	Boundaries of all protected areas	1: 250,000	Exclusion of ecosystem services not derived from protected areas	Driver et al. (2005)
Invasive alien plant species	Records of presence and abundance of species	Quarter-degree squares ($\sim 25 \times 25\,\mathrm{km}^2$)	Selection of important species that currently impact on ecosystem services	Henderson (1998)
	Crude maps of extent and density of infestations	1:250,000	Current impact of species on ecosystem services	Le Maitre et al. (2000).
	Estimates of potential distribution (based on climatic modelling)	Grid of $1\,\mathrm{km}^2$	Potential future impact of species on ecosystem services	Rouget et al. (2004)
Mean annual runoff	Estimates of mean annual surface water runoff	Quaternary catchments (varying in size, see text)	Basis for the calculation of impacts on surface water runoff	Midgley et al. (1994); Schulze et al. (1997)
Rivers	Maps of all major rivers	1:500,000	Definition of riparian zones	South African Department of Water Affairs and Forestry
Quaternary catchments	Nested subdivisions within primary, secondary, and tertiary catchments	1: 1 000,000	Basis for the estimation of impacts on water resources	South African Department of Water Affairs and Forestry
Livestock units	The carrying capacity of vegetation types in terms of large livestock units	1: 250,000	Demonstration of consequences of reduction in grazing capacity	Scholes (1998)

Table 2
The extent of five of South Africa's major biomes, showing the extent of transformation and conservation, rainfall and runoff characteristics, and the area of groundwater-dependant vegetation

	Biome				
	Fynbos shrublands	Grassland	Succulent karoo	Nama karoo	Savanna and thicket
Total area (km^2)	71,340	349,190	83,100	360,110	402,870
Area transformed (km^2)	22,700	102,110	4110	4550	59,590
Remaining natural area (km^2)	48,640	247,080	78,990	355,560	343,270
Area under conservation (km^2)	14,840	7430	4450	44,520	44,520
Mean annual precipitation (mm)	503	667	170	225	544
Mean annual runoff (mm)	95	77	4	8	36
Area of groundwater-dependant vegetation (km^2)	3750	2965	974	11,769	9993

>10% of the squares in each biome onto the current list. Examination of the current species distribution reveals that a relatively small number of species occupy >10% of each biome, but that these would account for most of the impacts by virtue of their dominance (Fig. 1). For example, out of 160 species in the fynbos biome, only 34, 17, and 4 species occupied >10%, 20%, and 50% of the quarter-degree squares, respectively. The threshold of 10% would thus capture a small but very important set of species in each biome. The potential for invasive alien plant species to extend their range has been estimated using climatic modelling at a $1 \times 1\,\mathrm{km}^2$ resolution (Rouget et al., 2004). We used these estimates to derive the future list by including all invasive alien plant species that had the potential to invade >20% of the biome concerned. Only areas classified as highly suitable to a species were used in this assessment. Potentially, many species will occupy a greater area in each biome than they currently do (Fig. 1).

Table 3

Important invasive alien plant species affecting the delivery of ecosystem services in five biomes in South Africa. Impacts on surface water runoff were calculated for landscape or riparian zones, or both, as indicated. See text for a detailed explanation of the classes of impact on grazing potential. Biodiversity impacts were rated as high or moderate if the impact was analogous to that of a plantation, or of degraded areas, respectively. A dash (–) indicates that the species was assumed not to affect the ecosystem service concerned

Species	Life form	Current and future biomes affected	Areas in which surface water is affected	Impact on grazing potential	Estimated impact on biodiversity
Acacia baileyana (Bailey's wattle)	Medium tree	Future: savanna, grassland, fynbos	Landscape and riparian	Very high	High
Acacia cyclops (red eye)	Medium tree	Current: fynbos; Future: fynbos, succulent karoo	Landscape and riparian	Very high	High
Acacia longifolia (longleaved wattle)	Medium tree	Current: fynbos; Future: fynbos, Nama karoo	Landscape and riparian	Very high	High
Acacia dealbata (silver wattle)	Medium tree	Current: grassland; Future: grassland	Landscape and riparian	Very high	High
Acacia decurrens (green wattle)	Medium tree	Current: grassland; Future: grassland	Landscape and riparian	Very high	High
Acacia mearnsii (black wattle)	Medium tree	Current: savanna, grassland, fynbos; Future: savanna, grassland, fynbos	Landscape and riparian	Very high	High
Acacia melanoxylon (blackwood)	Tall tree	Current: fynbos; Future: grassland, fynbos	Landscape and riparian	Very high	High
Acacia saligna (Port Jackson willow)	Medium tree	Current: fynbos; Future: fynbos, succulent karoo	Landscape and riparian	Very high	High
Achyranthes aspera (burweed)	Herb	Future: grassland	–	–	Moderate
Agave americana (American agave)	Succulent	Current: grassland, fynbos; Future: savanna, grassland, fynbos, succulent karoo, Nama karoo	–	Moderate	Moderate
Arundo donax (giant reed)	Tall grass	Current: savanna, grassland, fynbos; Future: grassland, fynbos	Riparian		High
Atriplex lindleyi (sponge-fruit saltbush)	Low shrub	Current: fynbos, succulent karoo, Nama karoo; Future: fynbos, succulent karoo, Nama karoo	–	–	Moderate
Atriplex nummularia (old man saltbush)	Low shrub	Current: succulent karoo; Future: fynbos, succulent karoo, Nama karoo	–	–	Moderate
Cortaderia selloana (Pampas grass)	Tall grass	Current: fynbos	–	–	Moderate
Caesalpinia decapetala (Mauritius thorn)	Shrub	Current: savanna		Very high	Moderate
Cestrum laevigatum (inkberry)	Shrub	Future: savanna	–	Moderate	Moderate
Chromolaena odorata (triffid weed)	Shrub	Current: savanna, grassland	–	Very high	High
Cuscuta campestris (common dodder)	Parasitic herb	Current: grassland; Future: savanna, grassland	–		Moderate
Datura stramonium (common thorn apple)	Annual	Current: fynbos	–	–	Medium
Echinopsis spachiana (torch cactus)	Succulent	Future: savanna, grassland, Nama karoo		Very high	Moderate
Eucalyptus camaldulensis (red river gum)	Tall tree	Current: fynbos; Future: grassland, fynbos, succulent karoo	Riparian	–	High
Eucalyptus grandis (rose gum)	Tall tree	Current: grassland	Riparian	–	High
Eucalyptus lehmannii (spider gum)	Medium tree	Future: fynbos	Landscape	High	High
Hakea drupacea (sweet hakea)	Tall shrub	Current: fynbos; Future: fynbos	Landscape	High	High
Hakea gibbosa (rock hakea)	Tall shrub	Current: fynbos	Landscape	High	High
Hakea sericea (silky hakea)	Tall shrub	Current: fynbos; Future: fynbos	Landscape	High	High
Ipomoea indica (morning glory)	Herbaceous climber	Future: savanna, grassland	–	–	Moderate

Table 3 (*continued*)

Species	Life form	Current and future biomes affected	Areas in which surface water is affected	Impact on grazing potential	Estimated impact on biodiversity
Jackaranda mimosifolia (jackaranda)	Tall tree	Current: savanna, grassland; Future: savanna, grassland	Landscape and riparian	Moderately high	High
Lantana camara (lantana)	Shrub	Current: savanna, grassland, fynbos; Future: savanna	–	Very high	High
Leptospermum laevigatum (Australian myrtle)	Medium tree	Current: fynbos; Future: fynbos	Landscape	Very high	High
Macfadyena unguis-cati (cat's claw creeper)	Climber	Future: savanna	–	–	High
Melia azedarach (Persian lilac)	Tall tree	Current: savanna, grassland, fynbos; Future: savanna, grassland	Landscape and riparian	Moderately high	High
Nicotiana glauca (wild tobacco)	Shrub	Current: savanna, fynbos, succulent karoo, Nama karoo; Future: savanna, grassland, fynbos, succulent karoo, Nama karoo	–	–	Moderate
Paraserianthes lophantha (stink bean)	Medium tree	Current: fynbos; Future: fynbos	Landscape and riparian	–	High
Pennisetum clandestinum (Kikuyu grass)	Grass	Current: fynbos	–	–	Moderate
Pinus elliottii (slash pine)	Tall tree	Future: savanna, grassland	Landscape	High	High
Pinus halepensis (Aleppo pine)	Tall tree	Future: savanna, grassland, fynbos, Nama karoo	Landscape	Very high	High
Pinus patula (patula pine)	Tall tree	Current: grassland Future: grassland	Landscape	High	High
Pinus pinaster (cluster pine)	Tall tree	Current: fynbos; Future: fynbos	Landscape	Very high	High
Pinus radiata (Monterey pine)	Tall tree	Future: fynbos	Landscape	Very high	High
Populus alba (white poplar)	Tall tree	Current: grassland	Riparian	–	High
Populus canescens (grey poplar)	Tall tree	Current: grassland, fynbos	Riparian	–	High
Prosopis glandulosa (mesquite)	Tall tree	Current: fynbos, succulent karoo, Nama karoo; Future: savanna, Nama karoo	Landscape and riparian	High	High
Prunus persica (peach)	Medium tree	Current: savanna	–	–	Moderate
Psidium guajava (guava)	Medium tree	Current: savanna, grassland; Future: savanna	–	High	Moderate
Pyracantha angustifolia (yellow firethorn)	Tall shrub	Current: grassland	–	Moderately high	Moderate
Robinia pseudoacacia (black locust)	Tall tree	Future: savanna, grassland	Landscape and riparian	Moderately high	High
Rubus cunefolius (American bramble)	Shrub	Current: grassland	–	Very high	Moderate
Rubus fruticosus (European blackberry)	Shrub	Current: grassland, Fynbos; Future: fynbos	–	Very high	Moderate
Salix babylonica (weeping willow)	Medium tree	Current: grassland; Future: grassland	Riparian	–	High
Senna didymobotrya (peanut butter cassia)	Shrub	Current: savanna; Future: savanna	–	Low	–
Senna occidentalis (wild coffee)	Shrub	Future: savanna	–	Low	–
Solanum mauritianum (bugweed)	Medium tree	Current: savanna, grassland, fynbos; Future: savanna, grassland	–	Low	Moderate
Solanum seaforthianum (Potato creeper)	Climber	Future: savanna	–	Low	–
Solanum sisymbriifolium (wild tomato)	Shrub	Future: grassland	–	–	Moderate
Xanthium strumarium (large cocklebur)	Annual	Current: savanna; Future: savanna, grassland	–	Moderate	–

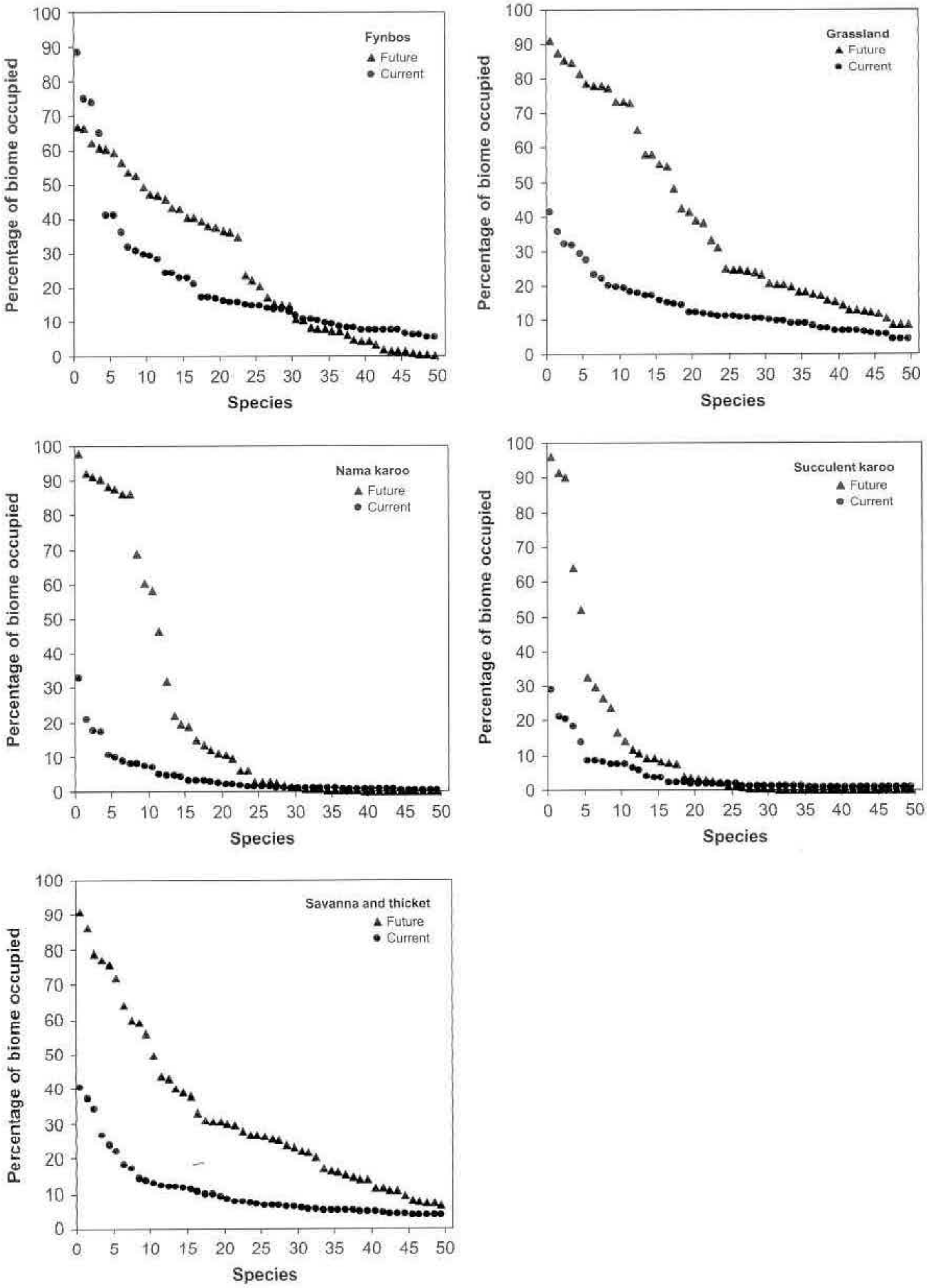

Fig. 1. Percentage of the biome occupied by the 50 most abundant invasive alien plant species in five biomes in South Africa. The current distribution was estimated from records of presence in quarter-degree squares, and the future distribution from climatic suitability modelling.

We used 20% as a threshold for selecting species for inclusion in the future list, and not 10% as in the case of the current list, given the greater degree of uncertainty involved.

For each biome, we created subsets of the current and future lists, consisting of those invasive alien plant species that would have an impact on each of the ecosystem services assessed. We also eliminated invasive species that were known to be under complete or substantial biological control (Zimmermann et al., 2004), as well as those that were known to be naturalised but not to be aggressively invasive in the biome concerned, or that were known to colonise disturbed areas only.

2.3. Selection of important ecosystem services

Many ecosystem services and categories of ecosystem services exist (Daily, 1997; de Groot et al., 2002; Millennium Ecosystem Assessment, 2005). In a similar fashion to the Southern African Millennium Ecosystem Assessment (Biggs et al., 2004), we limited our study to the provisioning ecosystem services—a category with good available data and high relevance to decision-makers. Within this category we selected ecosystem services that are supplied by largely untransformed natural areas and where we have sound knowledge of the impacts of invasive alien plants. These were the generation of surface water runoff, the recharge of groundwater, and the provision of grazing to domestic livestock. These services provide significant benefits to South African society and have been well studied and documented. Besides being a basic need for survival, water underpins agriculture, forestry, mining, and industry in South Africa, and is a limiting resource; in addition, many rural towns in western South Africa are dependent on groundwater (van Tonder, 1999). Grazing provided by natural vegetation also contributes significantly to livestock production in the country (Scholes, 1998).

This list of ecosystem services is not exhaustive and misses some key services where we do not have adequate data on their supply or on the impact of alien plants. Examples include fuel wood harvesting, medicinal plant supply, soil protection, and climate regulation, as well as ecosystem services generated by human-modified systems (such as crop production).

This study, like the Millennium Ecosystem Assessment (2005), sees biodiversity and its status as a necessary precondition to sustained ecosystem service supply. Thus, an assessment of the current and future impacts of alien plant invasions on biodiversity integrity was conducted to assess the integrity of the ecosystems and their ability to continue supplying other ecosystem services not assessed. Although there are circumstances where biodiversity can be a service itself, we did not consider it further in this way.

2.4. Impacts on surface water runoff

The species listed as being of importance to surface water runoff included species that could be classified as tall trees, medium trees or large shrubs according to the definitions given by Le Maitre et al. (2000). Each list was further subdivided, based on habitat records in the SAPIA database, and published lists (Nel et al., 2004), into those tree and shrub species that invade riparian areas, those that invade landscapes away from riparian areas ("drylands"), and those that invade both.

We used maps of the extent of invasive alien species infestations in each biome to estimate impacts on surface water runoff. These infestations were mapped at a scale of 1:250,000, and are a crude approximation of the extent and density of invasions of each species in the late 1990s (Le Maitre et al., 2000). The cover of each species on the current list was used to estimate the impacts in terms of reductions in surface water runoff, using the methods described by Dzvukamandja et al. (2005). This approach divides invaded areas into riparian strips and drylands. Invaders in riparian strips potentially have access to additional water from the river itself, to groundwater in the riparian strip and to lateral discharges of groundwater into the riparian zone. Their transpiration, and thus their impact on surface water flows, is limited only by the atmospheric vapour demand and by the physiology of the plant. The physiological limitations were catered for by assuming that the plant could only transpire at a proportion of the atmospheric demand. Transpiration by dryland invaders (and thus the reduction in surface water flows) was limited to a proportion of the pre-invasion runoff. The proportions were determined by the invader size class as defined by Le Maitre et al. (2000), and were 78%, 60%, and 23% for tall trees, medium trees, and tall shrubs, respectively. The reductions in surface water flows were calculated at the level of quaternary catchments (quaternary catchments are nested subdivisions within primary, secondary, and tertiary catchments, ranging in size from 5000 to 180,000 ha), and these were summed to determine the combined impact of all species in each biome.

The potential impact of future invasions was determined using a similar procedure, adapted to be compatible with the scale at which potential future invasions had been mapped. Estimates of reductions in surface water runoff were calculated for cells of one minute by one minute (approximately $1.8 \times 1.8\,\text{km}^2$). The mean annual runoff within each cell was obtained from Midgley et al. (1994). Reductions were estimated as above for those alien plant species designated as landscape invaders on the future list. As many species could potentially occupy the same grid cell in future, summing the estimated reductions for all species would result in an over-estimate of impacts. We therefore estimated the reduction associated with the single species that would cause the largest reduction in the grid cell concerned, and summed these estimates for each biome. Riparian zones were assumed to cover 1% of each grid cell in which rivers were located (the cover of riparian zones across the country amounted to this area on average, assuming that each riparian strip was 20 m wide). For each grid cell that contained at least one riparian invasive species, surface water runoff reduction was assumed to be 500 mm more than that of the vegetation that was replaced from the 1% deemed to be within the riparian zone. A reduction of 500 mm represents the estimated average annual water use from areas invaded by alien trees that have constant access to river water via bank storage. The estimates for the landscape and riparian reductions were combined to obtain an estimate of overall reduction.

2.5. *Impacts on groundwater recharge*

We confined our analysis of impacts on groundwater recharge to a subset of vegetation types mapped by Mucina and Rutherford (2004). These types included those with a high likelihood of groundwater dependence (riparian vegetation, alluvial and aeolian deposits where the groundwater is believed to be potentially within the rooting depth of at least the woody plant species, dolomitic and limestone areas, and dune vegetation). Deep-rooted invasive alien trees and shrubs would effectively reduce the recharge of groundwater aquifers in these vegetation types, assuming that they have access to water that would, under normal circumstances, filter through to groundwater rather than form part of surface water runoff. We assumed that invasive alien plants classified as tall trees, medium trees, and tall shrubs (Le Maitre et al., 2000) would reduce groundwater recharge by 20% of the mean annual runoff in the area concerned. This magnitude of reduction was based on comparisons of groundwater recharge rates between dune areas with no vegetation, natural vegetation and infestations of Australian wattles (Zhang et al., 2004). Estimates of current impacts were based on areas where groundwater-dependent vegetation and infestations of invasive alien plants (as mapped by Le Maitre et al., 2000) overlapped. Those associated with potential future impacts were based on the future potential distributions as mapped by Rouget et al. (2004a).

2.6. *Impacts on grazing*

The species listed as being of importance to grazing excluded those that would have little or no impact on grazing (for example, those species that only invade highly disturbed areas). Each species record in the SAPIA database is designated as very abundant, abundant, frequent, occasional, present, or rare, depending on the density of plants where the record was made. From the current list for each combination of species and abundance class, we used expert opinion to estimate the percentage by which an infestation of the species would reduce the grazing capacity of pristine vegetation. In order to do this, several experts familiar with the species and their effects in the field were consulted; these included field ecologists from the Centre for Invasion Biology (www.sun.ac.za/cib/) as well as researchers with decades of field experience in the biological control of invasive species. Species were classified into five broad types with regard to impact:

i. Very high—species that reduce the grazing potential by 80% when very abundant, by 20–50% when abundant or frequent, and by 5% when occasional.
ii. High—species that reduce the grazing potential by 60% when very abundant, by 15–30% when abundant or frequent, and by <5% when occasional.
iii. Moderately high—species that reduce the grazing potential by 40% when very abundant, by 10–25% when abundant or frequent, and by <2% when occasional.
iv. Moderate—species that reduce the grazing potential by 30% when very abundant, by 5–20% when abundant or frequent, and by <2% when occasional.
v. Low—species that reduce the grazing potential by 15% when very abundant, by 3–7% when abundant or frequent, and by <2% when occasional.

The impacts of these invasions in each of the biomes was assumed to be restricted to untransformed natural vegetation, excluding areas transformed by crop agriculture, plantation forestry, urban development, and protected areas (where livestock production for commercial purposes does not take place).

We used estimates of the mean livestock production (in large livestock units per km^2) to represent the potential of un-invaded vegetation to support livestock production (Scholes, 1998). The impact of current invasions of alien plant species on potential livestock production was estimated using maps of the extent of invasive alien species in each biome (Le Maitre et al., 2000). We estimated the impact of each species based on the density in which it was recorded, at a 1-min grid cell resolution ($1.8 \times 1.8\,\mathrm{km}^2$). The impact was then assumed to be that associated with the one species predicted to have the greatest impact on grazing in the grid cell concerned, and these estimates were summed for the biome as a whole. The potential impact of future invasions was estimated by assuming that the areas identified as highly suitable for a species (in terms of climatic suitability; Rouget et al. (2004)) would become densely invaded by that species. The impact was assumed to be that associated with the species with the highest potential impact predicted to occur in each grid cell, and these reductions in grazing potential were summed across each biome.

2.7. *Impacts on biodiversity*

The impacts of alien invasive plants on biodiversity are poorly understood (Richardson and van Wilgen, 2004). For the purposes of this study, we needed a spatially explicit estimate of changes in biodiversity integrity with changes in alien distributions. For this purpose the biodiversity intactness index (BII) developed by Scholes and Biggs (2005) proved useful. This index translates expert estimates of land use impacts on vertebrate and plant populations into a spatial estimate of biodiversity integrity. It is an aggregate index that combines information on ecosystem distribution, species richness and the extent and impact of major land uses on biodiversity. It is intended to provide an easy-to-understand overview of the state of biodiversity for policy-makers and the public. In essence, BII is a richness and area-weighted average of the impact of a set of land use activities on populations of plants, mammals, birds, reptiles, and frogs in a given area. If the population impact (I_{ijk}) is defined as the relative population of taxon i (as compared to the reference state) under land use activity k in ecosystem j, then BII gives the average remaining fraction of the populations of all species considered:

$$\mathrm{BII} = \frac{\sum_i \sum_j \sum_k R_{ij} A_{jk} I_{ijk}}{\sum_i \sum_j \sum_k R_{ij} A_{jk}},$$

where R_{ij} is the richness (number of species) of taxon i in ecosystem j and A_{jk} is the area of land use k in ecosystem j.

Data on the population impact (I_{ijk}) are currently not available, so Scholes and Biggs (2005) consulted three or more taxonomic specialists for each taxon to produce expert estimates of impact per land use per taxon per biome. These estimates were generated for protected areas, light use, cultivation, plantations, and urban and degraded areas. The index has been applied to South Africa by Biggs et al. (2006) based on the 1996 national land cover data which recognises areas of cultivation, plantations, urban development, protected areas, degraded areas and natural areas (equivalent to areas of light use). This data layer represents biodiversity intactness without invasive alien plants.

The lists of alien invasive plant species were then divided into two categories per biome. These were species which in dense stands would have impacts equivalent to those associated with plantations, or with degraded areas. As described above, several experts familiar with the species and their effects in the field were consulted when assigning species to the two categories.

The current extent of dense infestations per species was assessed using the estimates of Le Maitre et al. (2000). If the polygon of dense infestation was found to include any species from list above, it was categorised as a degraded area or plantation area depending on the species present. If both categories of species were present then the area was classified as a plantation. These areas were merged with the national land cover data layer and used to calculate the changes in biodiversity intactness. A similar procedure was used for the estimated future impacts of invasions, using data from Rouget et al. (2004).

3. Results

3.1. Determination of area at risk from invasion

The extent of terrestrial biomes in South Africa ranges from <7.5 to >40 million ha (Table 2). Our assessment sought to quantify the impacts of invasive species on ecosystem services arising from the untransformed areas of the biomes. The two karoo types are the least transformed of these biomes, with between 1% and 5% transformed by agriculture and urban development. About one third of the grassland and fynbos biomes, and 15% of the savanna biome, have been transformed. The savanna, fynbos, and Nama karoo biomes are reasonably well represented in the national network of protected areas, while the succulent karoo (5%) and grassland (2%) biomes have relatively little area under formal conservation. The fact that some biomes have only small areas under formal protection could have implications for their management. For example, clear and co-ordinated invasive alien plant control policies would be required to ensure their widespread implementation by larger numbers of landowners in biomes where levels of formal protection are low.

3.2. Selection of important invasive alien plant species

A total of 56 species were listed in the current and future lists as having important impacts on the delivery of ecosystem services (Table 3). Tall and medium trees (28 species) and shrubs (16 species) made up the bulk of species, while herbs, annuals and climbers (7 species), grasses (3 species) and succulents (2 species) accounted for the remainder. Many succulents from the genus *Opuntia* (cacti) were eliminated from the lists—although they are widespread, they are under effective biological control. We also eliminated many species that were widespread, or potentially widespread, either because they are invaders of disturbed areas only, or because they are known not to be aggressive invaders. Finally, the paucity of grasses in our lists is remarkable. Grasses are important, but often overlooked, elements of the South African invasive flora. Milton (2004) lists over 100 invasive alien species in South Africa, for example; these are, however, not adequately captured in the SAPIA database (which lists only 9 grass species), because of the difficulty of identifying such species.

3.3. Impacts on surface water runoff

The estimated annual reductions in surface water runoff as a result of current infestations of invasive alien plants ranges from 0.4 mm (rainfall equivalent) in the dry Nama karoo, to 15.2 mm in the fynbos shrublands. These estimated reductions amount to over 3000 million m^3 of surface water runoff annually (Fig. 2), most of which is from the fynbos and grassland biomes, and which represents approximately 7% of the runoff of the country (Le Maitre et al., 2000). If infestations of invasive alien plants were to reach their full potential, these impacts could increase to between 2.3 mm in the dry Nama karoo, and 38.5 mm in the grassland biome; the potential reductions could be more than eight times greater, at about 25,000 million m^3 of surface water runoff (approximately 58% of the surface water runoff of the country; Fig. 2). Most of this impact would be felt in the grassland biome.

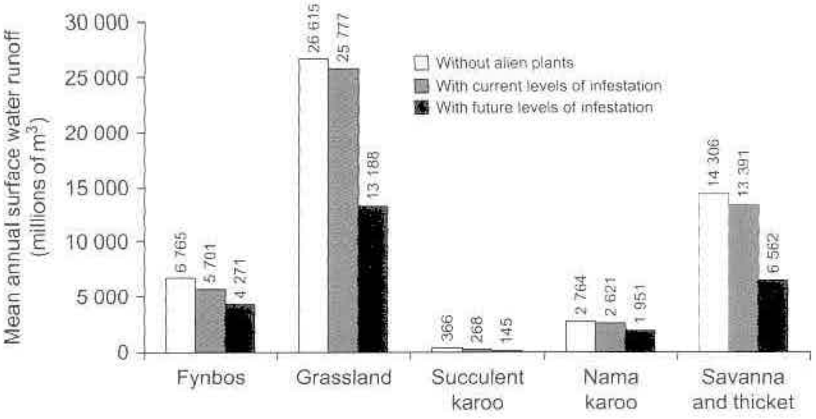

Fig. 2. Estimates of the current and potential impacts of invasive alien plants on surface water runoff in five biomes in South Africa.

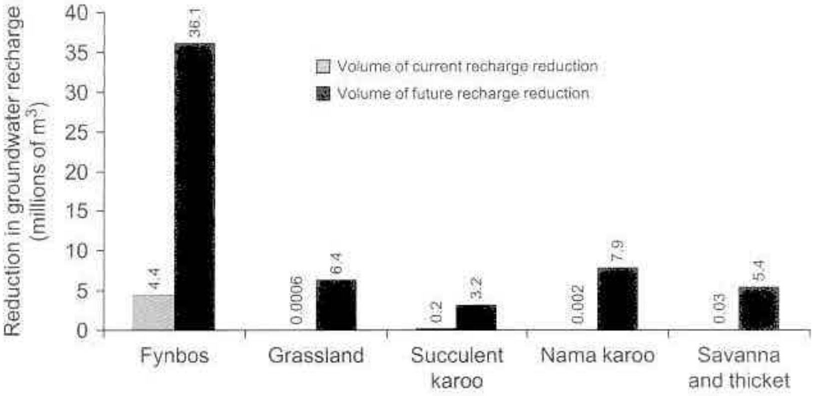

Fig. 3. Estimates of the current and potential impacts of invasive alien plants on groundwater recharge in five biomes in South Africa.

3.4. Impacts on groundwater recharge

The extent of groundwater-dependant vegetation was the greatest in the fynbos biome, where it accounted for >5% of the total area of the biome (Table 2). About 3% and 2.5% of the Nama karoo and savanna biomes, respectively, were designated as groundwater dependant, while the proportion of the succulent karoo and grassland biomes was about 1%. The estimated potential reductions in groundwater recharge are correspondingly highest (36 million m^3 annually) in the fynbos biome. The actual volumes are small, however, when compared to the estimates for surface water runoff, amounting to only 1.5% of the potential reductions in surface water runoff due to invasive alien plants (Fig. 3). The estimated potential reductions in the grasslands are relatively small compared to the potential reductions in surface water runoff. Similarly, the reductions in groundwater recharge in the two karoo biomes are small, but arguably more significant given that the importance of water in these arid ecosystems.

3.5. Impacts on grazing

The grassland, Nama karoo and savanna biomes would potentially support the largest number of livestock units in the country (Fig. 4). The estimated current reductions in the potential for these ecosystems to support grazing stock, as a result invasive alien plant infestations, amount to between 200 (in the Nama karoo) and 74,500 (in the fynbos) large stock units (Fig. 4). This amounts to just over 1% of the potential number of livestock that can be supported by these ecosystems. However, if infestations of invasive alien plants are allowed to reach their full potential, these impacts could increase to 71% of the potential.

3.6. Impacts on biodiversity

Current estimates of the BII range from 71% to 89% for the five biomes analysed (Fig. 5). These estimates take into account the conversion of natural landscapes by means of agriculture, forestry or urban development, as well as land degradation, but they do not account for the impacts of invasive alien plants. When the additional impacts of invasive alien plants are considered, estimates of the current levels for the BII only declined in the fynbos biome (from 73% to 70%; Fig. 5). This finding reflects the fact that the fynbos biome currently has the highest levels of alien plant infestations; this, in turn, is probably due to the considerably longer period of colonial settlement in the

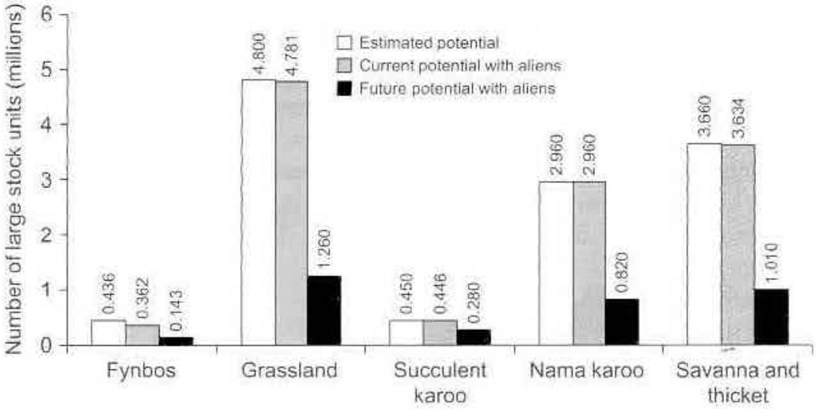

Fig. 4. Estimates of the potential numbers of large stock units that could be supported in five biomes in South Africa, the degree to which these numbers are currently and potentially reduced by invasive alien plants.

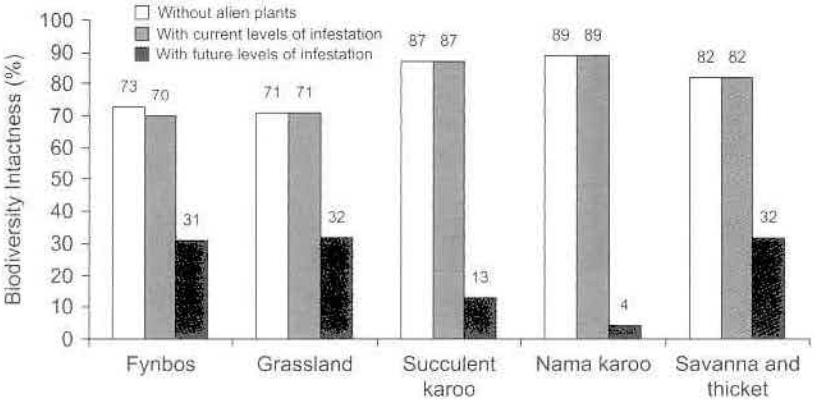

Fig. 5. Estimates of the current and potential impacts of invasive alien plants on biodiversity in five biomes in South Africa. Data are expressed as a "biodiversity intactness index" (Scholes and Biggs, 2005), which is the estimated proportion of remaining populations of vertebrates and vascular plants.

area. Under a scenario where invasive alien plants are allowed to reach their full potential, however, the values decline dramatically, to around 30% for the savanna, fynbos and grassland biomes, but to even lower values (13% and 4%) for the two karoo biomes, suggesting significant potential population declines of >90% in places.

4. Discussion and conclusions

4.1. The importance of large-scale assessments

Economic evaluations of the impacts of invasive alien plants are required for the formulation of appropriate approaches to the problem. Such evaluations must in turn be based on good estimates of the consequences in terms of ecosystem services. Many of the studies that have been done in this regard have been focussed at smaller spatial scales where good data are available (e.g., van Wilgen et al., 1997; Turpie and Heydenrych, 2000), or on a single species (e.g., de Wit et al., 2001; McConnachie et al., 2003). While these studies are useful, they do not support the higher-level estimates that would be required to formulate appropriate national policies for dealing with invasive species. Our study has provided estimates, albeit preliminary ones, at a biome-scale, demonstrating the feasibility of such approaches. The limited number of datasets available to do this evaluation also illustrates the difficulties facing those who wish to attempt higher-level assessments. First, good datasets on many ecosystem services are not available. Where they are available, they have not always been collected at the same scale, with the same degree of accuracy, or for a common purpose. These shortcomings require assessors to make assumptions that could compromise the reliability of estimates, or confuse comparisons.

Our results suggest that, while the current impacts of invasive alien plants are relatively low (with the exception of those on surface water runoff), the future impacts could be very high. In all likelihood, the current impacts have been underestimated, while future impacts may well have been overestimated because of our assumptions that all climatically suitable areas would become invaded. The data on the current extent of invasions are very coarse and incomplete, while those for the future are modelled using climatic suitability, and this approach produces a large estimate for cover. In addition, any analysis at a national level has to involve broad assumptions, as we have made in this study. These included, for example, the assumptions that only certain species would impact on ecosystem services; that all climatically suitable areas would become invaded; that particular levels of impact on grazing and groundwater recharge could be assumed; and that reductions in biodiversity resulting from invasions would be similar to those associated with other forms of degradation. The approach, however, has allowed us to produce estimates, albeit unsophisticated ones, at a national level.

4.2. *The serious nature of the problem*

Reductions in the provision of ecosystem services of the magnitude estimated in this study would generate significant, negative economic consequences. Whether or not they materialise depends to a large degree on whether or not the ecosystems at risk will suffer from the predicted levels of invasion. Are such levels possible? A number of points can be made in this regard. In the first place, many of South Africa's remaining natural ecosystems are relatively free of significant infestations of invasive alien plants at present (with the notable exception of the fynbos biome, where infestations of invasive plants are at much higher levels). The fact that many invasive plant species already occur in many areas at low densities, and are known to be able to develop into dense closed stands over time, suggests that an ongoing escalation in the level of infestations can be expected over time. The situation can also be expected to worsen as new invasive species become established. New invasive species will continue to arrive, and many potential invasive species are probably already here—but not yet invading. Many serious invasions have exhibited a "lag period" in which the introduced species may occur at very low population levels for several decades before becoming invasive, sometimes suddenly (Crooks, 2005; Pyšek and Hulme, 2005). This could be the result of exponential population growth, a period of selection of genotypes suited to the newly invaded environment, or the occurrence of a change in environmental conditions that constrain invasions. With the rapid growth in the rate of introduction of new species, most introductions of alien species have occurred recently. It is therefore likely that a large number of invaders are currently in their "lag period", and the rate of new invasive species problems will increase dramatically in future. Global changes, such as changes in climate and in the rates and magnitudes of biogeochemical cycles, may further worsen the situation, by bringing about conditions more favourable for invasions (Dukes and Mooney, 1999; Baruch and Jackson, 2005). Finally, our study has also only focussed on four ecosystem services, and the potential is there for the addition of many more; this would probably also increase the levels of estimated impacts on ecosystem services (even if some of these were positively affected by invasions), and situation could worsen as new species arrive and become invasive. We believe, therefore, that this problem is significant, growing in importance, and demanding of serious scientific attention at an appropriate level.

The seriousness of the predictions of impact can be illustrated with reference to water supplies. South Africa is a dry country, and like many others the demand for water resources often exceeds the capacity of ecosystems to provide them. While the country as a whole still has a water surplus, recent studies have shown that demand already exceeds supply in more than half of the 87 water management areas in South Africa (van Wilgen et al., 2007). Thus, any further reduction in water supplies as a result of watershed areas becoming invaded by trees and shrubs will seriously retard the prospects for economic growth. Similar statements could be made with regard to livestock production. Although estimates are difficult to make at a national level, livestock production from natural ecosystems generates in the order of R1.25 billion annually in South Africa (Department of Agriculture, 2005). A significant proportion of this economic benefit may well be lost as a result of invasion of rangelands by trees, shrubs, succulents, and unpalatable grasses. The impacts of reductions in biodiversity on the delivery of ecosystem services would require further study to be able to understand the important links.

Our assessment has attempted to quantify the impacts of invasive species (and, by proxy, the benefits of control) at a biome level. Managers of alien plant infestations would like to know, more exactly, where they should focus their efforts to maximise the benefits in terms of improved protection of ecosystem services. We have not attempted to address this issue here, but the dataset created as part of this project could feed into decision-support products developed for this purpose. For example, van Wilgen et al. (2007) used data on the distribution and impacts of alien plants to examine where such priorities should lie. Their approach identified priority areas that had not been identified as such, and predicted that their approach would provide decision-makers with an objective and transparent method with which to prioritise areas for the control of invasive alien plants. The explicit mapping of impacts on ecosystem services would provide important material in this regard.

4.3. *Levels of confidence in predictions*

Our data and approaches do not allow for the calculation of error estimates associated with predicted impacts. While the errors in these estimates could be large, the predicted impacts are of sufficient magnitude to suggest that, even with significant over-estimates, there is cause for serious concern; for example, even if the levels of impact are one tenth of those predicted, they would result in significant losses of benefit.

Future studies of this kind would be improved by the inclusion of a sensitivity analysis. There would be a number of ways in which this could be done. We have chosen those species that were expected to have the largest impacts on the ecosystem service concerned. In the event that the particular species did not prove to be invasive, sensitivity analysis could examine the impacts of species in declining order of predicted impact. For example, we assumed that future impacts on grazing would be associated with the one species predicted to have the greatest impact. This could result in an under-estimate (in cases where additional areas may be invaded by other species), or an overestimate (if the selected species fails to invade, and the impact reverts to the next-worst species). The levels of expected impact could also be varied in a sensitivity analysis (for example, by using categories for high, medium and low levels of impact). Finally, the possibility that future invasions could cover varying areas within the estimated climatically suitable habitat could be explored.

4.4. *Challenges for future research*

Conducting assessments at a national level will pose significant challenges for researchers. This assessment has highlighted some of these, which include:

i. the need for robust, comprehensive estimates of the distribution of invasive alien species, accompanied by approximations of the density of invasions. The development of such datasets would require a co-ordinated, national effort involving different land management agencies and other significant landowners. This underscores the importance of a holistic view of invasions and co-operation between authorities;
ii. the development of simple models that will allow for the estimation of impacts of invasions on important ecosystem services. The models should incorporate the ability to scale up from studies at smaller scales to produce estimates at, for example, the level of biomes or provinces;
iii. the development of techniques to estimate the rate at which invasive alien plants will spread. Our estimates of the potential future impacts of invasive alien plants are large, but there is no way of knowing when these levels of impact would be reached, given the inability to estimate rates of spread. One solution could be combine our findings with the opinions of an expert panel on probable spread rates and other important relevant variables to arrive at estimates; and
iv. the likely replacement of one invasive species by another. For example, if an important species is cleared from an area, or brought under biological control, the area may simply be invaded by another species, which could nullify the net benefits gained from control operations. Competition between different invasive alien plant species is also important in this regard. Relatively un-invaded areas may be threatened by several invasive species, each of which could have different impacts. The relative degree to which one or some of these species will eventually dominate a given area needs to be estimated to assess potential impacts.

We believe that addressing these issues is important. Accurate estimates of the ecological consequences (in terms of ecosystem services at a broad-scale) can only be made if the challenges outlined above are overcome. They can then form the basis for a rigorous economic assessment of consequences, the development of science-founded policies, and serve to ensure that adequate attention is paid to the issue at national levels.

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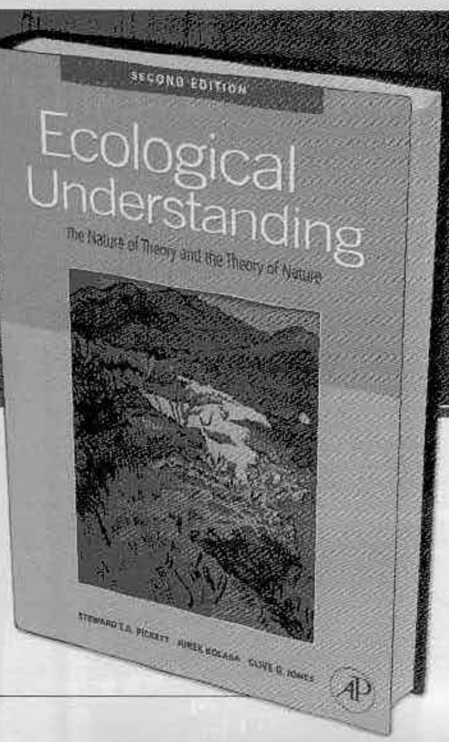
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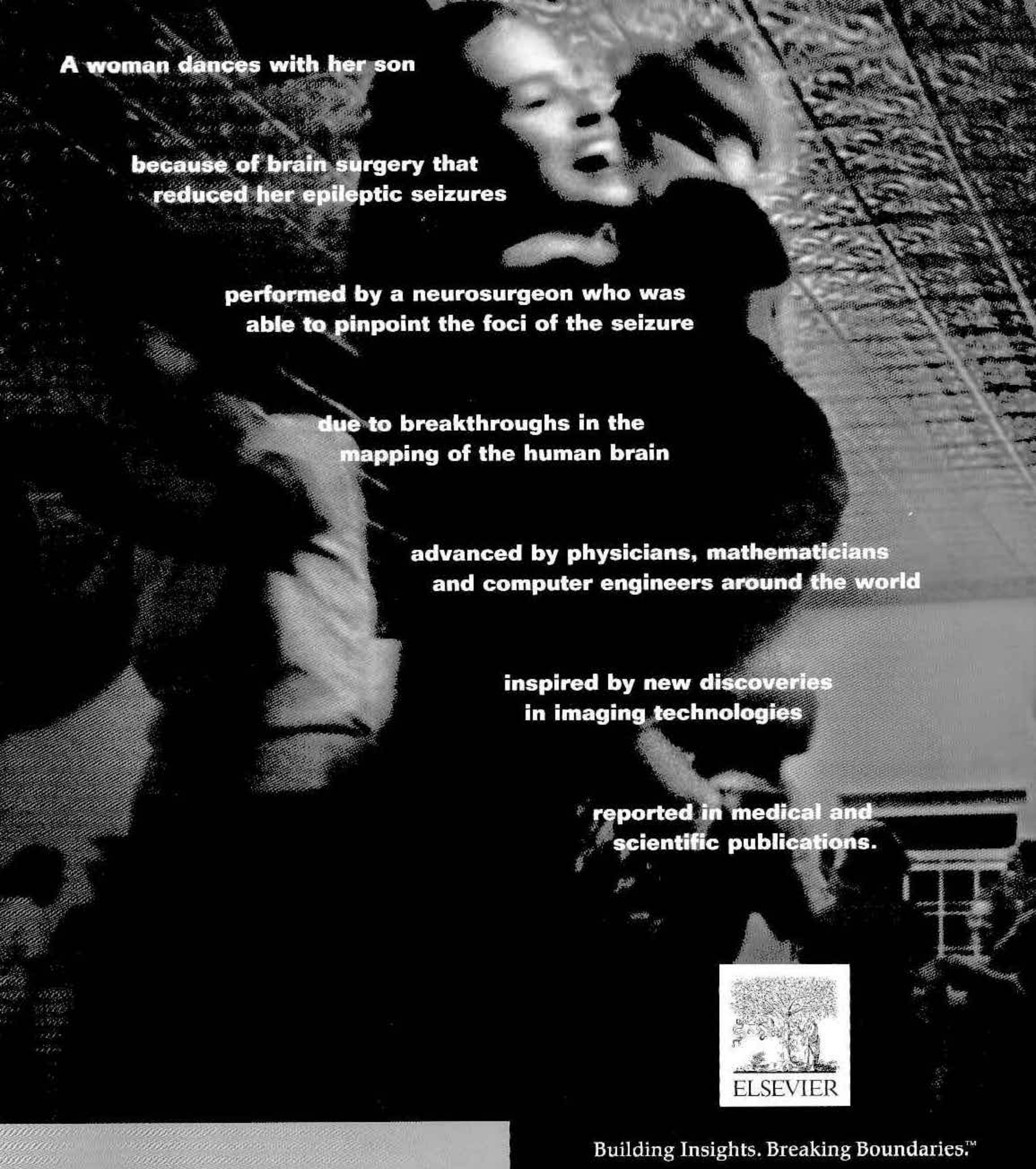
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because of brain surgery that
reduced her epileptic seizures
performed by a neurosurgeon who was
able to pinpoint the foci of the seizure
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