ALLOCATING BIOSECURITY RESOURCES IN SPACE AND TIME

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Invasive species can cause significant damage to natural environments, agricultural systems, human populations and the economy as a whole. Biological invasions are complex dynamic systems which are inherently uncertain and their control involves allocation of surveillance and treatment resources in space and time. A complicating factor is that there are at least two types of surveillance: active and passive. Active surveillance, undertaken by pest control agencies, has high sensitivity but generally low coverage because of its high cost. Passive surveillance, undertaken by the public, has low sensitivity and may have high coverage depending on human population density. Its effectiveness depends on the extent to which information campaigns succeed in engaging the public to help locate and report pests. Here we use a spatio-temporal model to study the efficient allocation of search and treatment resources in space and time. In particular we look for complementarities between passive and active surveillance. We identify strategies that increase the probability of eradication and/or decrease the cost of managing an invasion. We also explore ways in which the public can be engaged to achieve cost-effective improvements in the probability of detecting and eradicating a pest.

Key words: search theory, invasive species, dispersal, passive surveillance.

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Introduction

Invasive species are one of the leading causes of global ecological change (D'Antonio and Vitousek 1992; Wilcove et al. 1998; Olson 2006), causing significant losses through their effect on agriculture, human health and the environment (Williams and Timmins 2002; Sinden et al. 2005; Colautti et al. 2006). The spread of invasive species is facilitated by the increased movement of people, cargo and genetic material around the world and there is an expectation that climate change will further increase spread, by changing suitable habitat and causing adverse weather events that support the spread of disease vectors (Mooney and Hobbs, 2000; McNeeley et al. 2001).

Eradication can prevent much of the damage of an uncontrolled invasion (Veitch and Clout 2002; Simberloff 2003) and therefore is the primary goal of invasion managers where it is deemed to be feasible (Lodge et al. 2006). However, resources for conducting surveillance and treatment operations to control invasions are invariably limited, and eradication programs are expensive, therefore pursuing cost efficiency is essential for the success of these programs. Surveillance (or search time) is the main input for many types of invasions where no broad-scale treatment method exists (such as baits or chemicals spread from the air). In this study we focus on search effort as the input that determines eradication feasibility and assume that all detections are treated and that treatment has a given kill effectiveness (see Table 2). So the process is driven by search and detections, rather than situations where broad-scale treatment is available and can be applied independently of search and detection activities (see Spring et al. 2010).

Despite the complexity of the invasion process, a managed invasion can be described in terms of a few general features: reproduction, mortality, dispersal and habitat suitability. Those factors collectively determine the probability that propagules will spread to specific locations, become established and proliferate. Spatio-temporal models are well suited to represent that process. They are flexible, can be estimated from empirical data, and offer a rigorous quantitative basis for addressing the decision problems faced by invasion managers (Spring et al. 2010).

In an effort to identify factors that have the greatest impact on eradication feasibility we concentrate on the allocation of search effort based on four decisions: (i) The total amount of search effort available (M), (ii) the amount of search effort allocated per unit area (m), (iii) the radius of search around detections (r_m) and (iv) the number of repeat visits to previously visited sites (S_R). These four factors combine to determine the total area that is searched each year and the spatial arrangement and intensity of this surveillance. We base our analysis on the dataset of Cacho and Hester (2011). We conduct the analysis for two cases, one involving passive surveillance (reports from members of the public of encounters with the pest of interest, MAFBNZ 2008) and one where passive surveillance does not occur.

Method

An agency attempting to eradicate an invasion has four general decisions to make: the size of the budget; the expected program duration; the allocation of search effort in time and space, and the combination of passive and active surveillance to apply. We assume that, if passive surveillance is adopted the public is offered a bounty payment (C_B) for each detection reported to the agency. The total cost of the operation (C) depends on the amount of search undertaken by the agency, the number of reports by the public and the cost of treatment:

$$C = \sum_t \left[\left(N_{Pt} C_B + N_{At} m C_m + A_{Tt} C_T \right) + \sum_{\tau = t - S_R}^{t-1} N_{A\tau} m C_m \right] (1+\delta)^{-t} \tag{1}$$

where N_{pt} is the number passive finds reported in year t, N_{At} is the area searched (ha), m is the annual search effort (h/ha), A_{Tt} is the number of cells treated, δ is the discount rate, and C_B, C_m and C_T are the bounty payment ($/report), the cost of searching ($/h) and the cost of treatment ($/ha), respectively. The second summation term in (1) represents the cost of repeat searches that are undertaken as a result of detections in the previous S_R years. The variables N_{Pt}, N_{At} and A_{Tt} are calculated through stochastic simulations with a spatially-explicit model containing a heterogenous habitat (Figure 1) based on Cacho et al. (2010) and Cacho and Hester (2011).

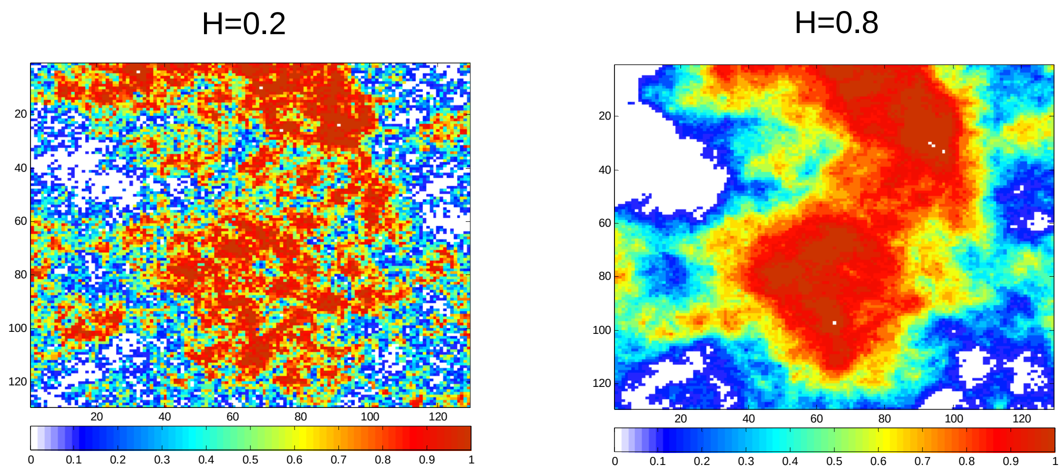

Figure 1. Sample of habitat suitability maps used in the model, the fractal dimension (H) determines the level of habitat clustering. The map on the left-hand side was used in this study.

From the variables in equation (1), N_{pt} is a function of passive detection probability (q) whereas N_{At} and A_{Tt} are functions of the search strategy. The total cost can be expressed as:

$$C = f\left(t, M, m, r_m, S_R \mid q, \delta\right) \tag{2}$$

where t is time in years; M is the budget expressed as the proportion of the total area that can be searched each year; m is the search effort applied per ha; r_m is the radius searched around detections and S_R is the number of repeat searches (see Table 1).

Table 1. Ranges of control parameter values used in Monte Carlo experiments of a managed invasion. The first two years of the simulation were discarded to reduce the influence of assumptions on the initial state of the invasion, this resulted in two datasets of 2400 observations each, one for the case with passive surveillance and one for the case without.

Parameter	Description	Regression ID	Range of values tested
t	years simulated	x_1	3, 4, …,10
M	total effort available per year (proportion of total area)	x_2	0.2, 0.4, 0.6, 0.8, 1.0
m	search effort per cell (h/ha)	x_3	2, 4, 6, 8, 10
r_m	search radius for detected sites (no. of cells)	x_4	1, 5, 10
S_R	number of repeat searches	x_5	0, 1, 2, 3
q	probability of passive detection	*	0, 0.5

* A separate regression was run for each of the two passive surveillance cases.

The probability of eradication was calculated as in Cacho and Hester (2011) and the data were used to conduct logistic regression based on a binomial distribution. Under that approach the outcome of a single Monte Carlo model run can be expressed as 1 (eradicated) or 0 (not eradicated) for each year of the simulation. Each experiment is then described by the number of cases that resulted in eradication out the 500 iterations that were run. The logistic formula is:

$$PE = \frac{e^{\mathbf{X\beta}}}{1+e^{\mathbf{X\beta}}} \tag{3}$$

where **X** is the design matrix and **β** is a vector of model parameters. Based on preliminary analysis we selected a quadratic function with interaction for the design matrix. For any given observation *j*, the elements of the *j*th row of the **X** matrix are:

$$X_j = \left(1, x_{1j}, x_{2j}, ..., x_{nj}, ..., x_{1j}x_{1,j}, x_{1j}x_{2j}, ..., x_{nj}x_{nj}\right) \tag{4}$$

where x_{ij} represents the control parameter *i* for experiment *j*. The *i* subscripts as described in Table 1 together with the range of values tested in Monte Carlo experiments. Other assumptions are presented in Table 2.

Using the same dataset, Cacho and Hester (2011) identified dominated strategies and derived efficient frontiers in terms of probability of eradication and total program cost (Figure 2). Here we build upon that analysis by fitting regression models that capture the essential features of a complex invasion process but solve fast enough to be used in optimisation analysis.

Table 2. Assumptions used in simulations.

Parameter	Value	Description
Environmental and biological assumptions:		
w	100	propagule pressure
α	0.02	habitat suitability (mean)
λ	5	effective sweep width (m)
p_k	0.98	treatment effectiveness
p_L	0.01	probability of long-distance jump
t_D	3	minimum time to discovery (y)
s	1000	search speed (m h^{-1})
γ	3.95	dispersal kernel parameter
D	10	maximum dispersal distance (number of cells)
Economic assumptions:		
C_B	500	cost of bounty ($ per find)
C_m	30	cost of search ($ h^{-1})
C_T	100	cost of treatment ($ ha^{-1})
ρ	0.06	discount rate
a	10,000	cell area (m^2)
T	15	planning horizon (y)

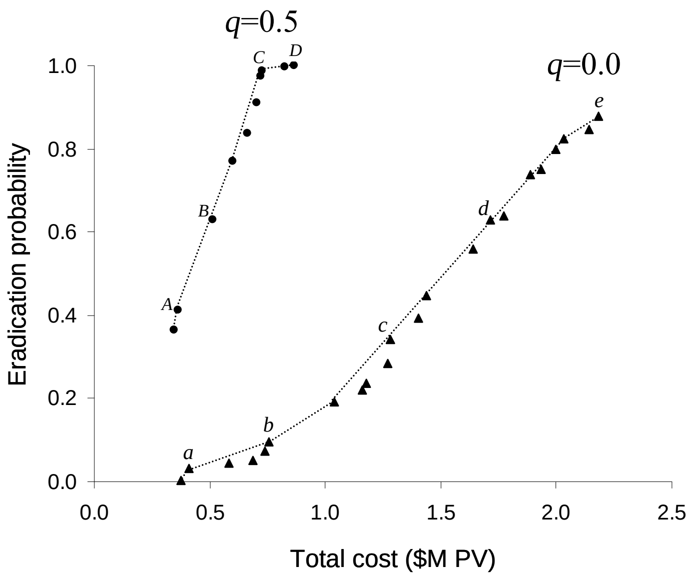

Figure 2. Efficient frontiers derived by Cacho and Hester (2011). Each point represents a different search strategy expressed in terms of total cost (in present-value terms) and probability of eradication. Two frontiers are shown, one for the case with no passive surveillance (q=0.0) and one for the case where passive detection probability is 0.5 (q=0.5). The full dataset used in their study forms the base of the analysis presented in this study. Source: Cacho and Hester (2011), p. 84.

Results and Discussion

The results of the logit model (3) are presented graphically in Figure 3. The predictive power of the model is considerably higher in the case with no passive surveillance as suggested by the scattering of points in Figure A as compared to B. In both cases (with and without passive surveillance) the predictions appear to be unbiased as indicated by the 45-degree line, so we can use them with some confidence to gain insight into the efficient allocation of search effort.

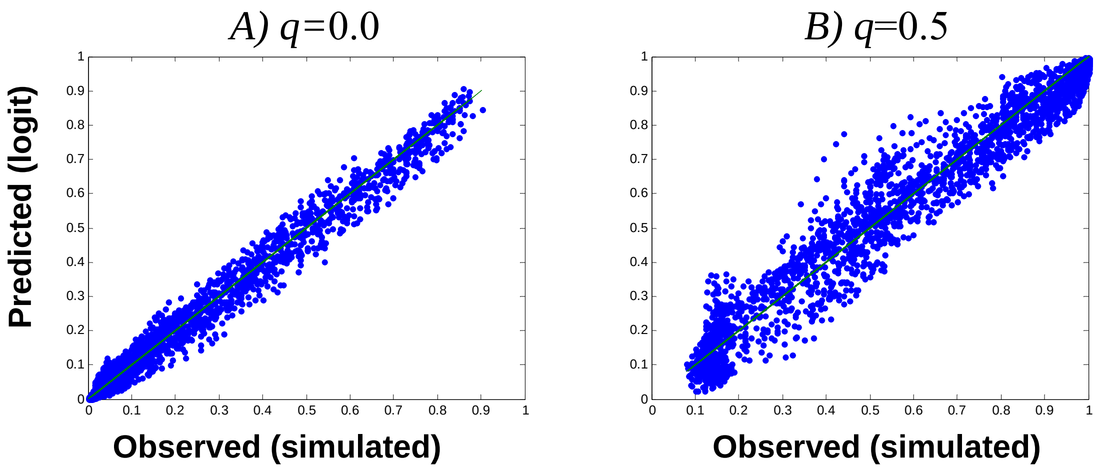

Figure 3. Results of logit models expressed in terms of observed vs. predicted results for two levels of passive surveillance. The 45-degree line represents perfect prediction.

The β values estimated through logit (equation 3) where used to numerically solve the problem:

$$\text{Max: } PE(m, r_m \mid t, M, S_R, q) \qquad (5)$$

The solution was obtained through nonlinear programming for alternative values of t and M, for the two levels of q (0 and 0.5) and with S_R=0 to avoid the confounding effect of repeat treatments on the annual allocation of search effort.

For convenience the annual budget is expressed as the proportion of the total area that can be searched (annual coverage) when one hour is allocated per ha. Plots of eradication probability against the budget (Figure 4), illustrate three interesting facts. First, the budget exhibits diminishing returns in terms of eradication probability. Second, passive surveillance has a dramatic effect on eradication probability both in terms of position and shape of the curves (compare plots A and B in Figure 4). Third, with a high budget (annual coverage >0.8) the invasion could be eradicated with high probability (PE>0.95) within six years if passive surveillance is available (plot B), but not without passive surveillance (PE<0.6 at year 6 on plot A).

Each point in Figure 4 is associated with a particular search strategy, which was identified as being optimal for the particular program duration and annual budget. A summary of those optimal strategies is presented in Table 3.

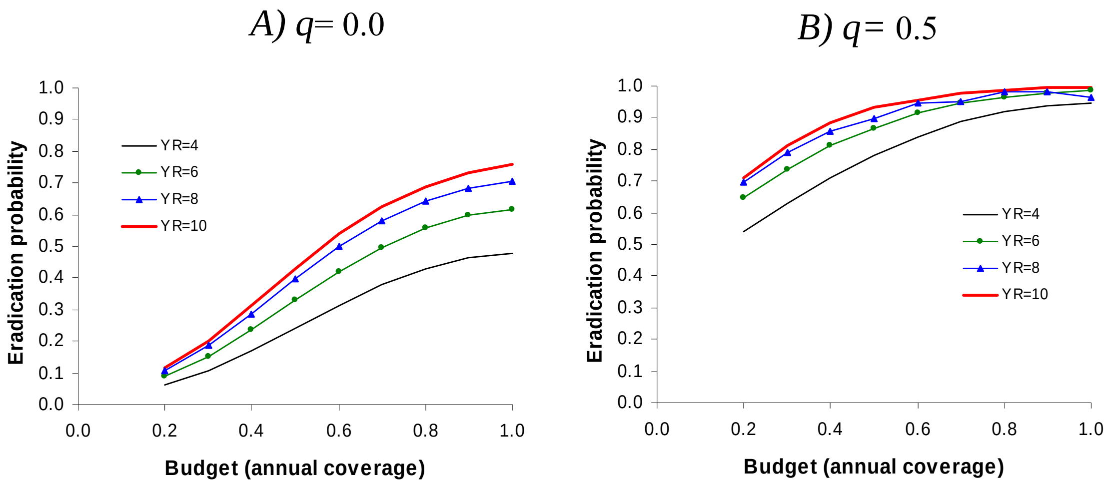

Figure 4. The effect of the budget on probability of eradication under optimal management of an invasion with four alternative program durations (YR = 4, 6, 8 and 10 years) and for two levels of passive surveillance (0.0 and 0.5). Results were obtained by solving the optimisation problem in equation (5) for the maximum probability attainable with a given budget.

Table 3. Results from the optimisation model in equation (5), expressed as means of optimal policies across budgets for each program duration.

Target year to eradication	Optimal strategy: Search effort (h/ha)	Search radius (m)	Area searched per find	Search intensity[a] (h/find)	Proportion searched[b]
q = 0.0					
4	7.1	1,040	337	3,494	0.21
6	7.2	1,060	356	3,785	0.23
8	7.3	1,060	352	3,731	0.23
10	7.1	1,080	368	3,983	0.24
Mean	7.2	1,060	353	3,748	0.23
q = 0.5					
4	7.1	880	245	2,159	0.13
6	6.4	820	212	1,746	0.11
8	5.9	880	245	2,164	0.13
10	6.0	810	206	1,662	0.10
Mean	6.4	850	227	1,933	0.12

[a.] The total number of search hours that are triggered when a new infestation is found under the optimal solution given the search radius and the search effort per ha. Note that because infested sites tend to form clusters, and a given parcel is not searched more than once in a given time period, not every single find causes that total area to be searched, as the overlapping area would be excluded from further searches.

[b.] Proportion of the total area that would be searched actively in response to a new find under the optimal solution given the search intensity and the size of the map (16,384 ha).

The mean search effort allocated per ha under the optimal solutions is quite high (7.2 and 6.4 for the cases with and without passive surveillance respectively). This is because the detectability is relatively low (λ=5 m in Table 2) and thus high coverage is required to obtain a high probability of detection (see Cacho et al. 2007 and Cacho and Hester 2011 for more details on this). The optimal search radius was approximately 1 km on average (1,060 m) with no passive surveillance and 850 m when passive surveillance was available. A smaller radius needed to be searched in the latter case because the public helped to detect new infestations. The decrease in search radius caused by the introduction of passive surveillance represents a reduction in the mean area that is searched in response to new detections (from 353 ha to 227 ha in column 4 of Table 3).

A convenient measure of search intensity is the number of search hours that are triggered by a new detection (column 5 in Table 3). Given the optimal levels of effort per ha (m) and search radius (r_m), the mean search intensity required under optimal management is considerably higher when no passive surveillance is available (3,798 h) than when it is (1,933 h). This means that the introduction of passive surveillance releases 3,798 – 1,933 = 1,865 h of active search time per detection on average. This is another way of measuring the value of passive surveillance in addition to the dollar value estimated by Cacho and Hester (2011).

The question that arises is: what would it take to improve reporting by the public and achieve the desired level of passive surveillance? The problem is not trivial. The probability of passive detection may be enhanced through awareness campaigns and bounty schemes that provide an incentive to members of the public to search for and report detections, but the influence of communication activities on passive detection probability is not easy to describe or measure. Empirical measures of passive detection probability are not available in the literature to our knowledge.

The literature on biosecurity community engagement and pro-environmental behaviour (eg. Kruger et al 2010, Stern 2000, DEFRA 2008) suggests that the response of the public to these activities is likely to depend on a range of factors that can be divided into five groups: (1) attributes of the pest; (2) attributes of the public communication programme; (3) situational attributes of people; (4) individual attributes of people; and (5) attributes of the areas in which people live, such as the amount and type of public space. These features are heterogeneously distributed in space and time and their distribution is unknown and difficult to measure.

Concluding Comments

This paper builds upon previous work on search theory and allocation of effort to manage biological invasions. A key feature of our approach is the use of a measure of detectability of the invasive organism, which enables us to calculate the search effort required to achieve a target probability of eradication, and from this we calculate the maximum eradication probability that can be achieved with a given budget. The optimisation exercise reported here produced useful insights regarding the intensity of search. We explored variations of two control variables: search effort per hectare and search radius, for different budgets. We found that the introduction of passive surveillance changes not only the shape but also the position of eradication probability functions with respect to the budget. The nature and consequences of these changes need to be studied in more detail.

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