

Report Cover Page

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APPLICATION OF SEARCH THEORY TO INVASIVE-SPECIES CONTROL PROGRAMS		
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Summary		
<p>In this study we develop a spatially-explicit bioeconomic model of a biological invasion. The model integrates search theory, population dynamics and economic principles.</p> <p>We address questions such as minimising the cost of eradication, minimising time to eradication or maximising the probability of eradication with a given budget. We develop simple decision tools to evaluate the minimum amount of funds that should be spent in information campaigns to enhance passive surveillance.</p> <p>We derive trade-off curves to identify sets of efficient search and control strategies in terms of costs and probability of eradication. This tool will enable agencies to undertake useful policy analyses and contribute to the planning process.</p> <p>We also develop an optimisation tool based on a genetic algorithm to find better search strategies in terms of three decisions: search effort allocated per site, buffer surveillance radius and number of repeat visits.</p> <p>Our results provide useful insights into the design of efficient invasive-species control programs and suggest areas for further research and possible application of our tools to actual invasions. Among other outputs, this project delivers better ways to leverage and justify requests for funds to control biological invasions.</p>		
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1. Executive Summary

Invasive species include plants, animals and micro-organisms not native to an area. Invasive species can cause significant damage to natural environments, agricultural systems, human populations and the economy as a whole. The main constraint to eliminating invaders is generally finding them rather than killing them. Once an invasion is found it can usually be successfully treated and destroyed.

Biological invasions are complex dynamic systems with many sources of uncertainty and may exhibit strong geographical variation. Fortunately, the essential features of biological invasions can be distilled down to parameters that describe rates of spread and growth, habitat suitability, vulnerability to control techniques, and severity of damages caused. Similarly, the essential features of control programs can be distilled down to parameters that describe the types and amounts of resources available, the effectiveness and costs of surveillance and control options, and the constraints imposed by legislative and environmental restrictions. This opens the door for developing models as management tools. Modelling the spread of invaders to assist in mitigating the ecological and commercial impacts of biological invasions allows us to identify economically-efficient strategies for slowing or reversing the spread of invaders.

The methodology used in this project is based on a spatially-explicit bioeconomic model that integrates search theory, population dynamics and economic principles. Search theory is a technique developed for search and rescue and military operations, and which has been recently applied to the control of biological invasions. The technique offers simple and convenient descriptions of detectability of a target and probability of detection as affected by search effort. We also account for the influence of habitat suitability on the progress of an invasion.

We address questions such as minimising the cost of eradication, minimising time to eradication or maximising the probability of eradication with a given budget. We develop simple decision tools to evaluate the minimum amount of funds that should be spent on information campaigns to enhance passive surveillance. We derive trade-off curves (efficient frontiers) to identify sets of search and control strategies that are efficient in terms of costs and probability of eradication. Our efficient frontier provides a useful policy tool that can be derived for any given surveillance strategy and for any given planning horizon, thereby enabling agencies to undertake sophisticated policy analyses with simple decision tools derived from complex, realistic models.

We develop an optimisation tool to find efficient search strategies in terms of three decisions: search effort allocated per site, buffer surveillance radius and number of repeat visits. Results provide useful insights into the design of efficient invasive-species control programs and suggest areas for further research and possible application of our tools to actual invasions.

Our results emphasise that both active and passive surveillance have an important role to play in invasive-species control, and that the probability of eradication is enhanced by combining both surveillance methods. Among other outputs, this project delivers formal tools, based on biology and economics, to leverage and justify requests for funds to control biological invasions.

2. Introduction

Invasive species are recognised as an important threat to global biodiversity (Vitousek et al., 1996) and are responsible for large economic losses (Liebhold et al., 1995; Liebman et al., 2001). Biological invasions are complex dynamic systems with many sources of uncertainty and generally exhibit strong geographical variation. Modelling the spread of invaders to assist in mitigating the ecological and commercial impacts of biological invasions allows us to identify strategies that are likely to be most effective in slowing or reversing the spread of invaders. In most non-agricultural situations, the main constraint to eliminating invaders is not killing them but finding them. Once an invasion is found it can usually be successfully treated and destroyed.

The probability of finding an organism through active search by a pest-control agency in a target area is affected by the detectability of the organism and the amount of search effort applied per unit area. With a limited budget, search effort can be allocated for broad coverage, with only a small amount of effort per site but covering a large area. Alternatively more search effort can be applied per site, resulting in less sites being able to be searched. The strategy selected is likely to affect the risk that the invasion will spread outside the containment area. There is a clear trade-off between intensity of search and the extent of area searched. Understanding this trade-off can lead to improved chances of controlling or eradicating invasions. Similar questions were studied by Hauser and McCarthy (2008, 2009), who developed a model to allocate effort in space to minimise expected management costs. Their model takes account of environmental benefits and the ease of detection of the invader. The study reported here complements their work.

As an option to avoid spending large amounts of money searching for invaded sites over a large area, pest management agencies use ‘passive surveillance’; reports from members of the public of encounters with pests, to assist in surveillance and control. The Ministry of Agriculture and Forestry Biosecurity New Zealand (MAFBNZ) describes passive surveillance as ‘[s]urveillance that relies on members of the public, industry groups, plant or animal health professionals and/or laboratories reporting suspected cases of plant or animal disease or the presence of a pest at their discretion.’ (MAFBNZ 2008, p. 29).

Passive detections are often the method by which an invader is first recognised in a country or region. For example, the initial detection of the European wasp (*Vespula germanica*) in Western Australia occurred following a private submission of a wasp for identification (Davis and Wilson, 1991). This initial report subsequently led to the discovery of five nests and the implementation of an eradication campaign. Another example is the initial discovery of the red imported fire ant (*Solenopsis invicta*) in Australia, following submission of two separate samples of the ant by members of the public. The initial reports led to the discovery of two epicentres of infestation and the establishment of the Red Imported Fire Ant (RIFA) Eradication Program (Jennings, 2004). The recent passive detection of Khapra beetle in Perth and mango leaf gall midge on Horn Island in Queensland are two more examples of the important role the community can play in the early detection of invasive species (Beale et al. 2008).

Passive surveillance during eradication programs has proven to be very important: records from the campaign to eradicate the European wasp from Western Australia show that the public are responsible for finding 90% of the infestations in new areas (Davis and Wilson, 1991); reports of fire ants by the public have resulted in detections of half the outlying populations of the ant (Jennings, 2004); and the Four Tropical Weeds Eradication Program (4TWP) in Queensland obtained information for more than a quarter of the locations of weeds in the program due to detection by members of the public (Brooks and Galway, 2008).

Given the difficulty and expense of finding organisms through active search, and the potential importance of passive detections, an understanding of both types of surveillance can help develop useful decision tools. Cacho et al. (2006, 2007) adapted search theory (a technique used in search and rescue and military operations) to the control of biological invasions. Their model assumed a homogeneous search area where population density could increase but did not consider spatial spread. In this report we extend their model by applying the search algorithm to multiple sites within a landscape and representing spread through space as well as time. We apply the model to a hypothetical invasion and determine the probability and the potential costs of eradication for various surveillance and control strategies. We develop simple decision tools to evaluate the minimum amount of funds that should be spent in information campaigns to enhance passive surveillance.

We then extend the basic model to derive economic efficiency measures. First we produce trade-off curves that allow us to identify sets of search and control strategies that are efficient in terms of costs and probability of eradication. Then we develop an optimisation tool to find better search strategies in terms of three decisions: search effort allocated per site, buffer surveillance radius and number of repeat visits. Results provide useful insights into the design of efficient invasive-species control programs.

We conclude the report by suggesting areas for further research and possible application of our tools to actual invasions.

3. Methodology

The methodology used in this project is based on a spatially-explicit bioeconomic model that integrates search theory, population dynamics and economic principles (Figure 1). Maps of habitat suitability, land ownership, land use and other factors are read into the model. Search parameters are also read into the model to estimate the probability that an infestation will be found as a function of search effort. The population dynamics of the invader is driven by a dispersal kernel that results in spread through space. The simulation model is used to generate results on area invaded, eradication probability, number of detections, allocation of search effort applied and other relevant variables. These physical results are then processed and combined with economic parameters to estimate costs and other measures of performance. In extensions of the model an optimisation feedback loop is introduced to identify economically-efficient search and control strategies by manipulating search parameters. The model components are described in the following sections.

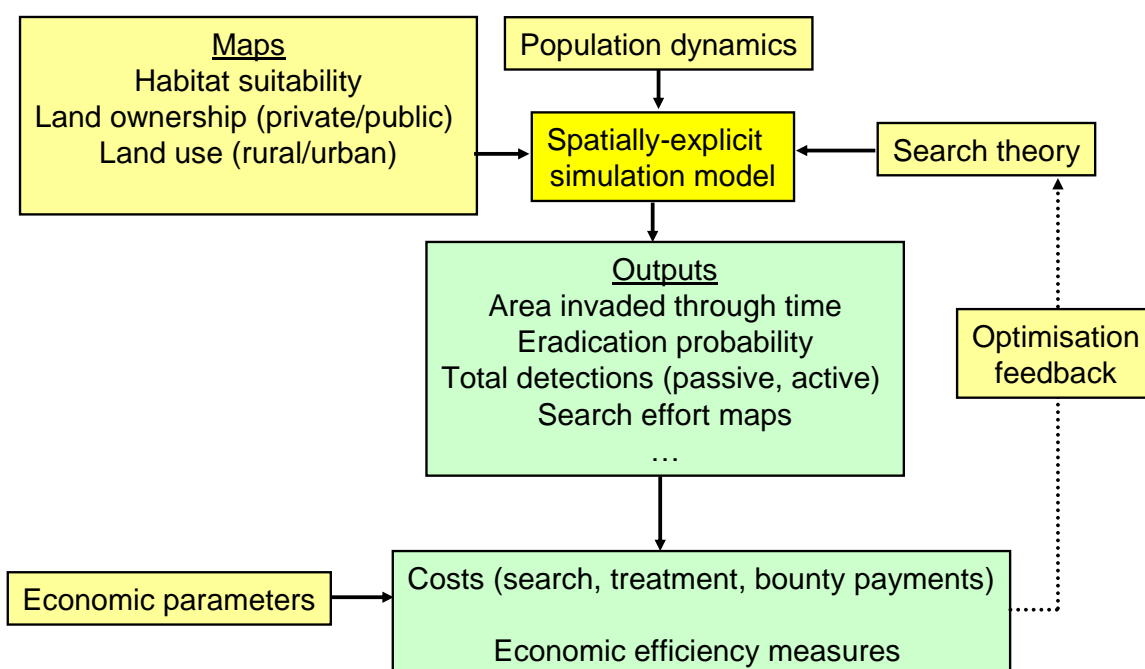


Figure 1. Overview of model design.

3.1 Model Description

The landscape is represented as a grid of n_r rows and n_c columns containing $n=n_r \times n_c$ square cells of area a . Variables associated with this grid are represented as column vectors of dimension n with corresponding grid cells identified by index $i=1, \dots, n$; numbered down the rows and then across columns. This arrangement simplifies numerical calculations and allows cells that do not belong to the map to be excluded from calculations (i.e. it accommodates non-rectangular maps). This arrangement also reduces computer memory requirements to run the model. These vectors are converted into matrices of dimension $n_r \times n_c$ for display as maps.

The state of cell i is given by its invasion status, represented by the binary variable x_i , (1=presence, 0=absence). The state of the invasion is contained in column vector \mathbf{x} , with elements x_i .

Cells have the following attributes:

- Habitat suitability (α_i), contained in vector $\boldsymbol{\alpha}$, represents the probability that a propagule landing on a cell will become established ($0 \leq \alpha_i \leq 1$).
- Detectability (λ_i), contained in vector $\boldsymbol{\lambda}$, is the effective sweep width (see below) measured in metres from the search path, λ_i depends on target characteristics, environmental conditions and searcher ability.
- Search speed (s_i), contained in vector \boldsymbol{s} , is the speed (in m/h) at which the cell can be traversed following standard search procedures, it depends on characteristics of the environment, such as slope, roughness etc.
- Urban status (u_i), contained in vector \boldsymbol{u} is a binary variable (1=urban, 0=rural).
- Ownership type (o_i), contained in vector \boldsymbol{o} is a binary variable (1=private, 0=public).

3.1.1 Dispersal

An invasion can be introduced in random locations or seeded on selected cells. An invaded cell produces w propagules per time period, and these propagules spread to neighbouring cells¹. The distance between cells (d_{ij}) determines the proportion of propagules from cell i that reach cell j according to a dispersal kernel. A Cauchy kernel was assumed, where the probability that a propagule originating in cell i and moving in direction θ will land on cell j is given by:

$$k_{ij}(\theta) = \frac{\delta_{ij}}{\sum_{l=0}^D \delta_{il}} \quad (1)$$

where D is the maximum dispersal distance and

$$\delta_{ij} = \frac{1}{1 + \left(\frac{d_{ij} \sqrt{a}}{\gamma} \right)^2} \quad (2)$$

where γ is a dispersal parameter. For convenience in the mapping process d_{ij} is measured in terms of number of cells and converted to metres in (2) based on the area (a) of a cell. A Cauchy kernel was selected because it is easy to compute and has heavy tails so it can capture long distance spread. Any kernel can be applied in the model simply by changing a function call in the code. The dispersal kernel assumed here is presented in Figure 2A

Upon model initialisation, an adjacency matrix (\mathbf{A}) of dimensions $n \times n$ is created, whose element A_{ij} represents the probability that a propagule originating in cell i will land on cell j .

¹ The number of propagules produced by an invaded cell (w) is constant, because the invasion state is a binary variable representing absence or presence and does not measure population density. This is a simplification that does not capture the increased number of propagules that would be produced by a cell that contains a denser invasion. However, exponential growth still occurs because the increasing number of invaded cells in the absence of control produces proportionally larger number of propagules. The use of presence/absence to describe invasion status is computationally convenient and it is suited to answering a number of important questions without the need for additional complexity, but there are cases where modelling local population density is important. This is discussed later in this report.

Each row \mathbf{A}_i is created by identifying the cells that are located within a circle of radius D from i and applying the kernel (1) to each cell in this set. The resulting values are then normalised so that $\sum_j A_{ij} = 1$.

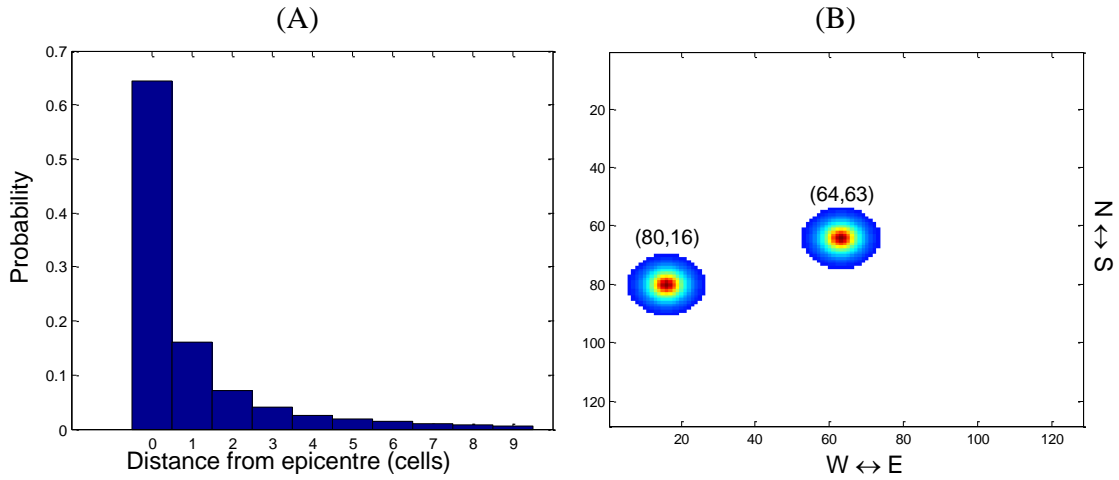


Figure 2. The dispersal kernel (A) and dispersal probabilities contained in the adjacency matrix (B), two arbitrary points are shown on the map.

Figure 2B shows a graphical representation of two rows of \mathbf{A} ; the rows were rearranged for mapping in two dimensions so $i = 1280$ for the circle labelled (80,16) and $i = 4032$ for the circle labelled (64,63). The probability values within each coloured circle add up to 1.0.

The probability that a given site will be invaded depends on both the number of propagules landing on it and its habitat suitability. In matrix notation:

$$\mathbf{p} = 1 - \exp(-\boldsymbol{\alpha}'\mathbf{o}\mathbf{n}) \quad (3)$$

$$\mathbf{n} = (\mathbf{x}'\mathbf{w})\mathbf{A} \quad (4)$$

The invasion probability vector \mathbf{p} contains a probability map that incorporates the combined effect of invaded sites (\mathbf{x}) and habitat suitability ($\boldsymbol{\alpha}$). A sample invasion probability map (the two-dimensional representation of \mathbf{p} for a random initial \mathbf{x}) is presented in Figure 3.

To represent dispersal, \mathbf{p} is compared to a vector of uniform random numbers \mathbf{r} and the new state of each cell is set according to the rule:

$$x_i = 1, \text{ if } r_i \leq p_i \quad (5)$$

otherwise x_i remains in its current state. Long-distance dispersal can occur with probability p_L independently of the dispersal kernel, as may occur when propagules are transported by road, water, or other means. This is represented by drawing a vector of uniform random numbers \mathbf{v} , with the same number of elements as the number of invaded sites. A long distance jump occurs for each case where:

$$v_i \leq p_L \quad (6)$$

The destination of these jumps is selected randomly within \mathbf{x} . Stochastic dispersal simulation through time is executed by applying (3) to (6) iteratively, resulting in an invasion state trajectory \mathbf{x}_t .

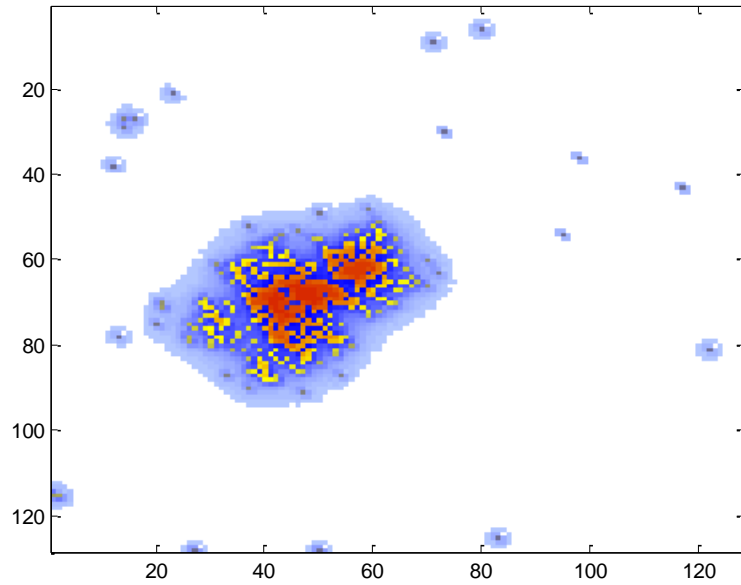


Figure 3. Sample invasion probability map.

3.1.2 Surveillance

An invaded cell can be detected through passive surveillance with probability (q_i) or through active surveillance with probability (z_i).

In passive surveillance the public detects an invader and reports it to the relevant agency. The probability of passive detection (\mathbf{q}) depends on the urban and ownership attributes of cells; for any cell i :

$$q_i = p_p(u_i, o_i) \quad (7)$$

Each year, search effort is invested in the following activities: (i) searching sites where treatment has occurred in the recent past (repeat search); (ii) in response to reports from the public (follow-up search); and (iii) through independent surveillance in public land not previously searched during (i) or (ii) (active search). The order of priority of these activities can be controlled by the user; in this application we apply them in the order given above.

The probability of detection through active surveillance is calculated based on search theory (Cacho et al., 2006, 2007). Search theory is based on the concept of coverage, defined as the ratio of the area actually searched over the total area to be searched. The probability that an invasion in cell i will be detected depends on the search effort applied m_i (h/cell), the speed of search s_i (m/h), effective sweep width λ_i (m) and the area of the cell (m^2):

$$z_i = 1 - \exp\left(-\left(\frac{s_i m_i \lambda_i}{a}\right)\right) \quad (8)$$

The expression within the inner brackets in (8) measures coverage: the numerator is the area effectively searched (m^2) as the product of distance traversed ($s_i \times m_i$) times effective sweep width (λ_i); the denominator is the area of the cell (m^2). A plot of equation (8) is presented in Figure 4A.

Effective sweep width (λ_i) measures the detectability of the target. It is derived from a lateral range curve which shows the probability that a target will be detected as a function of its

lateral distance from the searcher (Figure 4B). The efficiency of search per unit of distance covered is given by the area under the curve. The value of λ is computed by constructing a rectangular box of height 1 and lateral range equal to that at which the number of missed detections (b) within this range equals the number of detections (a) outside the range (Figure 4B). We could replace area b with area a and have the same number of total detections, thus a standard rectangle can characterise detectability for a given search method applied in a given environment. Effective sweep width is the width of the box in Figure 4B.

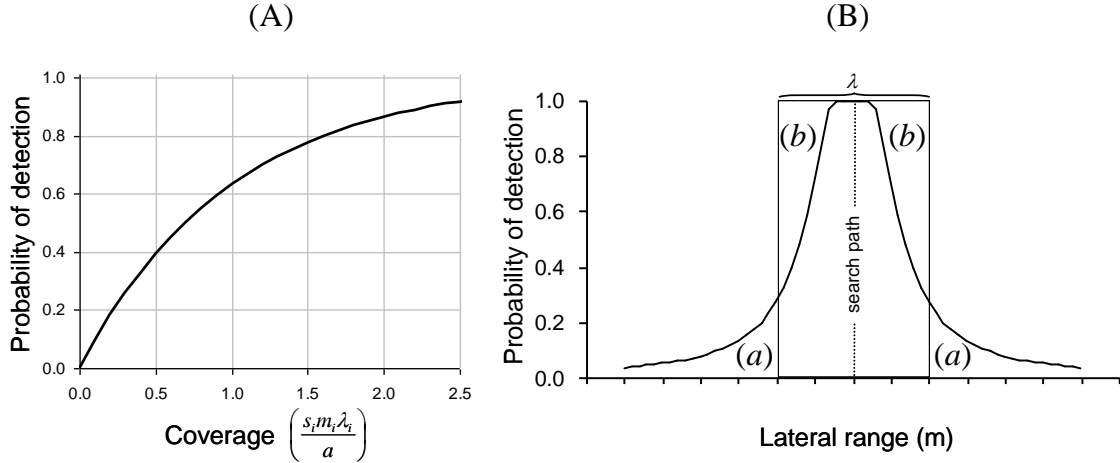


Figure 4. (A) the detection curve represented in equation (7) and (B) the lateral range curve used to generate λ .

We assume that, to encourage passive detections, the public is offered a bounty payment (C_B) for each detection reported to the relevant agency. The total cost of the operation is given by the number of passive reports, the amount of surveillance undertaken by the agency and the cost of treatment. Total cost in terms of present value is:

$$C = \sum_t \left[\left[(N_{pt} C_B + N_{at} m C_m + A_T C_T) + \sum_{\tau=t-S_R}^{t-1} N_{a\tau} C_m \right] (1 + \beta)^{-t} \right] \quad (9)$$

where N_{pt} is the number of cells where a passive find is reported in year t ; N_{at} is the number of cells where search takes place; A_T is the area treated as a result of the three types of search; β is the discount rate; and C_B , C_m and C_T are the bounty payment (\$/report), the cost of searching (\$/ha) and the cost of treatment (\$/ha), respectively. The second summation term in (9) represents the cost of repeat searches required as a result of detections in the previous S_R years.

We assume that only a portion (p_B) of passive detections are reported. If a passive detection occurs in a private parcel the invasion may be destroyed, but not necessarily reported. If the passive detection occurs in a public parcel it is destroyed only when reported. This covers the situation where a person may eliminate a pest from their backyard but they may not inform the authorities and therefore no follow-up searches would occur in adjacent areas. This option can be turned on or off depending on the type of pest. For example the discovery of wasp nest in a backyard may compel a person to destroy it, but the discovery of a weed may not.

3.2 Numerical Application

In order to test the model and design decision tools it is useful to have a ‘world’ with realistic attributes but which can be manipulated to represent any landscape pattern of interest. In our model the world is defined in terms of the five maps described earlier: habitat suitability,

detectability, search speed, urban status and ownership type. To create a world, these attributes could be allocated randomly, in the desired proportions, to cells in the map grid. However, purely random spatial patterns are not generally realistic in a landscape sense. Fractal algorithms can generate random worlds that possess realistic landscape structure. The mid-point displacement method (Saupe, 1988) is a simple and popular algorithm used for this purpose. The midpoint-displacement algorithm is a two-dimensional stochastic process defined by two parameters: variance, which determines the spread of values generated, and H , which determines the fractal dimension of the landscape. H can take values in the range of 0.0 (weak spatial autocorrelation) to 1.0 (strong spatial autocorrelation).

We used a midpoint-displacement algorithm (implemented based on the pseudocode presented by Saupe, 1988) to create a hypothetical world. Figure 5 shows four maps of private/public ownership generated by controlling the fractal dimension and the proportion of privately-owned parcels. This approach allows us to generate worlds that contain the same frequency distribution of attribute values but different levels of clustering. In future work this will allow us to study whether certain landscape features affect optimal decision rules. Our world had dimensions 129×129 ($n_r=n_c=129$), with each cell representing one hectare ($a=10000 \text{ m}^2$); therefore the total number of cells is the same as the number of hectares ($n = n_r \times n_c = 16641$). The dimension of the world was arbitrarily decided but constrained by the fact that the fractal algorithm used creates grids of dimension $(N+1)^2$, where $N = 2^y$. We set $y=7$ as a compromise between creating a world large enough to contain interesting spatial features but small enough to allow fast solution of the dispersal model. The map on the top left of Figure 5 was used in the simulations reported later. Other world attributes were initially assumed to be homogeneously distributed across the landscape to test the model in the absence of confounding factors.

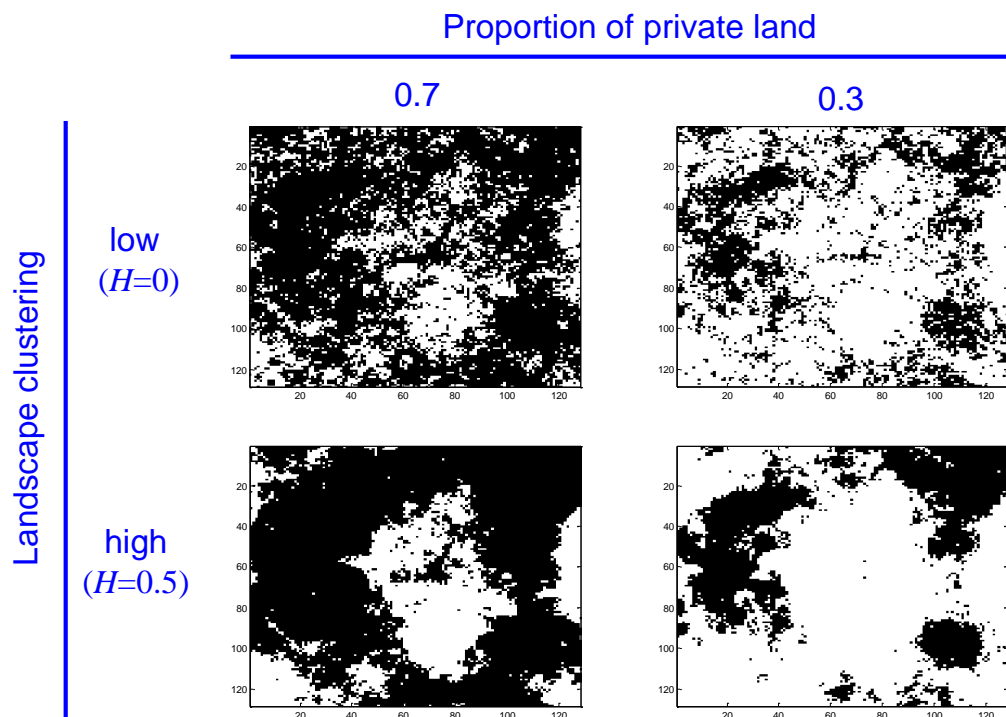


Figure 5. Landscape maps showing private (black) and public areas (white) with various combinations of fractal dimension (D) and proportion of private land.

The model is implemented in Matlab (The Mathworks, 2002). A verbal description of the numerical model operation is presented in the Appendix. We assumed that active-independent search by the pest-control agency occurs only in public land unless a detection is made (either by a private citizen or through active search), in which case an intensive search is conducted in all parcels within a specific radius (r_m) of the detection site, regardless of land class. The parameter values used in base-case simulations are presented in Table 1. The population parameters were roughly based on the red imported fire ant invasion in Brisbane, using anecdotal evidence and reports from QDPI, rather than analysis of actual data. The effective sweep width parameter (λ) was arbitrarily set a 5m as a conservative assumption regarding the detectability of nests. This low value may apply to small, young nests, but it is likely that large nests will have a larger value of λ , particularly when found in clusters. The Passive detection probabilities (0.3 and 0.1 for urban and rural areas respectively) were set at plausible values appropriate as a starting point for the analysis. These values are later changed as needed to explore interesting situations from a management standpoint.

Table 1. Parameter values used in the base case

Parameter	Value	Description
w	100	number of propagules produced by invaded cells
$p_p(1,1)$	0.3	probability of passive detection, (urban, private)
$p_p(1,0)$	0.1	probability of passive detection, (urban, public)
p_L	0.02	probability of long-distance jump
M	0	total effort available (h)
α_i	0.02	habitat suitability parameter
λ_i	5	effective sweep width (m)
s_i	1,000	search speed (m/h)
m_i	2	search effort applied per cell (h)
t_D	10	time period when invasion is discovered
γ	3.95	dispersal kernel parameter
D	10	dispersal distance (no. of cells)
p_k	0.98	probability of killing treated invasions
p_B	1	proportion of passive detections reported
r_m	5	search radius for reported sites (no. of cells)
S_R	3	number of repeat searches
C_B	500	cost of bounty (\$ per find)
C_m	30	cost of search (\$/h)
C_T	100	cost of treatment (\$/ha)
β	0.06	discount rate
a	10,000	cell area (m ²)
T	15	planning horizon (y)

The model was run for 500 Monte Carlo iterations and a planning horizon (T) of 15 years. Let

$$X_t = \sum_i x_{it} \quad (10)$$

represent the total area invaded at time t for a single iteration of the model. X_t is a measure of performance used to calculate eradication probabilities. Eradication was defined as absence of invaded sites after T years of simulation (i.e., where $X_T=0$).

3.3 Optimisation

Any invasive-species control program should aim at achieving optimal resource allocation for given goals and constraints. The most common objectives in such programs are the

maximisation of the benefit/cost ratio (or a similar measure of net benefit) and the minimisation of total cost (the sum of search, control and damage costs). The main constraint is generally the budget, but there may be others such the number of person-hours available per time period, the control technologies available, and environmental restrictions on the operation of the program. The decision variables are generally related to surveillance and treatment as the control options.

Dynamic optimisation techniques are well suited to answering such resource allocation questions (see for example Shea and Possingham, 2000; Odom et al., 2003; Cacho 2006; Regan et al., 2006). Within this class of techniques one that stands out is Stochastic Dynamic Programming (SDP), a powerful and flexible method of deriving decision rules based on the state of the system at any time. The main limitation of SDP is the ‘curse of dimensionality’ (Bellman, 1957), which arises because the state space increases quadratically as the number of possible states increases. SDP is not well suited to the spatially-explicit case where the number of possible states is very large². An option to overcome this limitation is to use the spatial model to generate results that are then aggregated into simplified state variables. Examples of this approach include the categorisation of patch ‘invadedness’ into just three states (Bogich and Shea 2008), and the use of invasion density and area invaded generated from a spatial model to describe an invasion in simple terms (Hyder et al. 2008).

Here we follow an alternative approach, based on embedding the spatial model within the optimisation algorithm. Our decision variables are the search effort applied per cell (m), the size of the radius searched when an infestation is discovered (r_m), and the number of repeat visits to previously treated sites (S_R); the last two variables are integers. The general objective is to maximise the expected progress towards eradication at the minimum possible cost, where progress is defined by the size of the invasion at time T relative to its size at time 0. The problem is to maximise:

$$F = \left(\frac{\bar{X}_0 - \bar{X}_T(m, r_m, S_R)}{(C(m, r_m, S_R))^v} \right) \quad (11)$$

Subject to the model described in (1) to (9) and where \bar{X}_T is the mean size of the invasion calculated from the set of 500 X_T values generated by a Monte Carlo simulation. The numerator in this equation is directly related to success in controlling the invasion (smaller invasions at T result in larger F) and the expression becomes negative when the invasion is growing. Cost as a denominator scales this measure, introducing a penalty for strategies that are effective but too expensive.

The solution to this type of optimisation problem is generally based on algorithms such as Newton’s method and its variations for smooth objective functions, or polytope methods (i.e. simplex) that require no smoothness conditions on the objective function (Judd, 1998). However, neither class of method works well when decision variables are integers. The binary-string genetic algorithm we apply here overcomes this limitation. Genetic algorithms (GA) are well suited to maximise functions that are highly non-linear or which have a large number of control variables (Cacho and Simmons 1999). They have been applied to a wide range of problems in agriculture and natural resource management (Mayer 2002), including to the management of invasive species (Taylor and Hastings, 2004). They have also been applied

² Consider our case with 16641 cells, each of which could be in either of two states (0,1); a complete description of possible states would require 2^{16641} values and the transition probability matrix would require the square of this number multiplied by the number of possible decisions.

to the derivation of search paths in complex environments (Kierstead and DelBalzo, 2003). There are different types of GA, but all of them contain the elements of evaluation, selection, crossover and mutation (Goldberg, 1989). These elements are explained below in terms of our model.

3.4 The Genetic Algorithm

The GA model consists of a population of 20 ‘individuals’ representing possible solutions to the optimisation problem. Each individual is assigned starting values for three ‘genes’ representing the control variables: m (search effort applied per cell), r_m (search radius around known infestations) and S_R (number of repeat searches). The two latter variables are constrained to integer values $r_m \in (0,1,\dots,7)$ and $S_R \in (0,1,2,3)$. These values can be represented as 2-bit and 3-bit binary strings respectively (which allow a total of 2^2 and 2^3 possible values to be represented). The control variable m is a non-negative real number (representing search hours per hectare), but in the GA it is discretised and represented as an 8-bit binary string. The real-valued parameter m is mapped into this discrete space, which contains 256 points. With $0 \leq m \leq 10$, this results in sampling intervals of 0.0392 h (i.e. $10/(256-1)$). The binary strings representing the three genes for each individual were concatenated horizontally, resulting in $2+3+8 = 13$ bits per individual. Hence the population of 20 possible solutions is represented as a (0,1) matrix of dimension 20×13 . Two such individuals are represented in Figure 6.

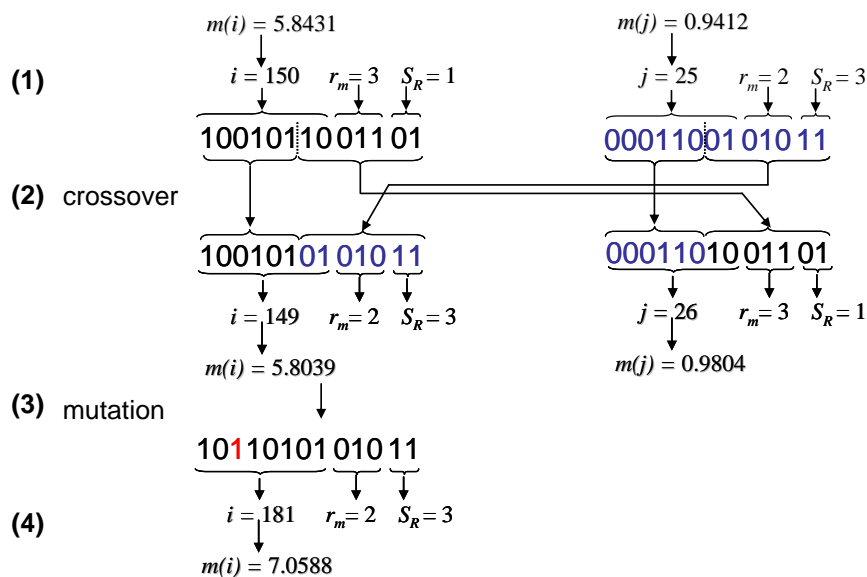


Figure 6. Representation of genetic algorithm showing (1) mapping from decimal to binary numbers, (2) crossover, (3) mutation and (4) mapping from binary to decimal.

The initial values of the three control variables for each individual in the population are drawn from a uniform distribution and mapped to the corresponding binary strings (Figure 6). The three parameters contained in the binary strings are mapped back into their decimal equivalent when used as input to the simulation model.

At the end of n simulations of T years the fitness of each individual is calculated through equation (11) based on the values of m , r_m and S_R contained in the individual’s genes. Individuals are then selected for reproduction using classical roulette wheel selection, where the probability of selection is proportional to the fitness of the individual relative to the rest of

the population (Mitchell, 1997, 166-167). Under this approach individuals can be selected more than once for reproduction, and genes belonging to individuals that are not selected disappear from the population.

After selection, cross-over occurs (Figure 6), with each pair producing two offspring and then disappearing, leaving the population size in the second generation the same as in the first. The worst performing individual of the new generation is then replaced by the best performing individual from the previous generation, this ensures the best solution found so far is not lost from the population. Crossover allows transmission of genes from one generation to the next and facilitates evolution of agents better adapted to their stochastic environment. The crossover operation makes copies from the genes of the two parents using the ‘bit string swapping’ mechanism described in Goldberg (1989) and elsewhere. The probability of single-point crossover occurring was set at 0.6, which means that there was a 0.4 probability of offspring being identical to their parents.

Pairing and crossover ensure two important things happen in the GA model. The first is, based on the fitness function (11) poor performers are removed from the population so eventually only the fittest survive. The second is, because pairing involves the whole population, inferior genes can survive, albeit in proportions decreasing with each generation, and hence the model has a ‘genetic memory’. However, a gene eventually disappears if it does not contribute to overall population fitness.

A proportion of the new generation may undergo random mutation of one or more of its genes. Mutation consists of flipping a random bit (ie. a zero changes to a one and vice-versa) in the binary representation of the parameters. As this evolutionary process moves through time, the genetic make-up of the population converges to values of m , r_m and S_R which provide the best control strategy for the given parameters (Table 1). Convergence in a GA can be declared when the entire population has evolved to the same genetic make-up, within the desired tolerance. The probability of mutation means that new genes may emerge at any time and this can prevent early convergence of the population.

In summary, the aim of our GA is to identify optimal search and control strategies that minimise the cost of management of the pest while maximising the likelihood of eradication. The GA starts with a population of ‘random individuals’, each containing starting values for three ‘genes’: search effort applied per cell (m); the size of the radius that is searched when an infestation is discovered (r_m); and the number of repeat visits to previously treated sites (S_R). Pairs of individuals are selected for reproduction based on their fitness (equation 11). Over successive generations the fitness of the population improves until the genetic makeup of the population converges to values of m , r_m and S_R that provide optimal or near-optimal solutions. The genetic algorithm parameters used later are presented in Table 2.

Table 2. Genetic algorithm parameters

Description	Value
Population size	20
Number of generations	50
Crossover probability	0.6
Mutation probability	0.6
Lower, upper bound of m	0, 10
Lower, upper bound of r_m	0, 7
Lower, upper bound of S_R	0, 3

4. Results and Discussion

The model was initially run for the base parameter values (Table 1), where active search is applied only in response to detections associated with passive surveillance and repeat searches. Additional search was applied if the follow-up to those detections (the search of radius r_m) resulted in additional detections, but no independent active search was applied ($M=0$). Results show that the invasion is unlikely to be controlled for the base case (Figure 7A), as the expected area invaded, $E(X_t)$, exhibits an increasing trend between years 5 and 15. In a subsequent model run, passive detection probability in private parcels was increased to 0.7 (from the base 0.3) while other parameters were kept at their base values. This resulted in effective control in the sense that $E(X_{15}) < X_0$ (Figure 7B). At this level of passive detection there was a positive probability that the invasion would be eradicated, as indicated by the lower 95% confidence limit.

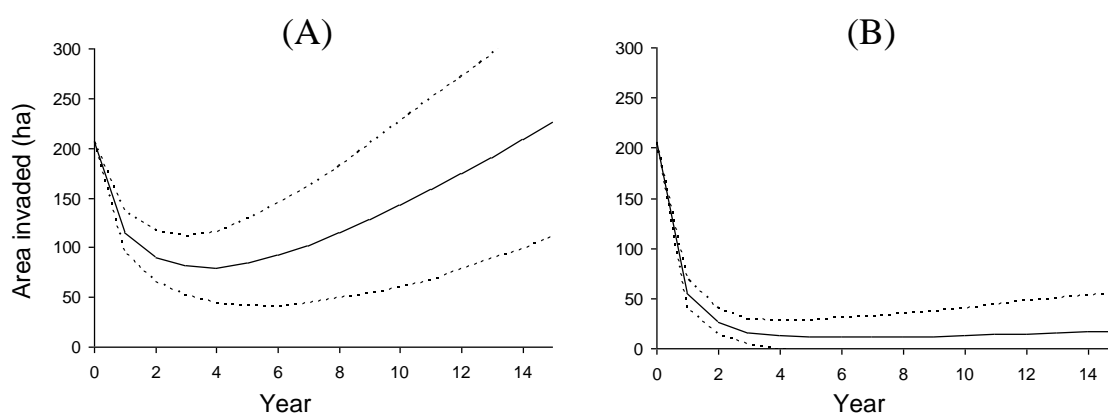


Figure 7. Expected invasion time trajectories, $E(X_t)$, for two different values of passive detection probabilities in private land (A) $pp=0.3$, (B) $pp=0.7$; dotted lines are 95% confidence limits.

Summary statistics for the cases illustrated in Figures 7A and 7B are presented in Table 3 (labelled *Base* and *Passive* respectively). In addition, we introduced active search of 6554 hours per year, enough to cover the equivalent of 0.2 of the total area at the given search effort per cell ($m=2$), this case is labelled *Active* in Table 3. Increasing passive detection probability (p_p) from 0.3 to 0.7 caused the expected cost of the eradication program to decrease substantially, from \$2.34 million to \$0.80 million, and the expected final area invaded to also decrease, from 225.54 to 16.97 ha (Table 3). The overall cost of eradication decreased at higher p_p because the pest was found (and controlled) earlier, so invasions were smaller and program duration was shorter. Similarly, introducing active search to the base case caused the expected final area invaded to decrease, from 225.54 to 30.96 ha, but the cost of the eradication program increased by about 40%, from \$2.34 million to \$3.34 million (compare *Base* against *Active* in Table 3). The overall cost of eradication increased because of the substantial expenditure on search effort (\$3.17 million).

These results show that increasing passive detection probability can produce substantial cost savings. But enhancing passive detections would require public information campaigns and the costs associated with this are not considered in Table 3, which includes only the costs of search, control and bounty payments. Although the cost of increasing the probability of passive detection is unknown, a lower bound can be placed on this expenditure based on economic efficiency criteria. The difference in cost between *Base* and *Passive* is \$1.54 million; this would be the minimum amount the agency should be prepared to spend to

achieve the prescribed increased in passive detection probability. The optimum may be higher than this as discussed below.

Table 3. Results associated with Figure 4.

	Scenario:	<i>Base</i>	<i>Passive</i>	<i>Active</i>
<i>Assumptions</i>				
Passive detection probability				
private land, $p_p(1,1)$		0.3	0.7	0.3
public land, $p_p(1,0)$		0.1	0.1	0.1
Active search effort				
hours (M)		0	0	6554
proportion area covered		0	0	0.2
<i>Results (means of 500 iterations)</i>				
Total cost (\$M)		2.34	0.80	3.34
Bounty cost (\$M)		0.31	0.19	0.16
Search cost (\$M)		2.01	0.60	3.17
Treatment cost (\$M)		0.02	0.01	0.01
Final area invaded, $E(X_t)$		225.54	16.97	30.96

4.1 How much to spend enhancing passive surveillance?

Consider the effect of marginal increases in passive detection probability on the cost of controlling the invasion calculated by the model (Figure 8). The cost of eradication decreases at a decreasing rate as passive detection probability increases. The overall cost of eradication decreases because the pest is found and controlled earlier than in the absence of passive surveillance. As discussed above, achieving such increases in p_p would require public information campaigns and the cost associated with this activity was not included in the analysis. The actual cost of such campaigns would depend on the behaviour of individuals and community groups and their response to information and monetary incentives. As already discussed, we can estimate the minimum amount an agency should be willing to invest in enhancing passive surveillance by calculating the difference in present value of total program costs between the present situation and the target situation.

The vertical difference between the horizontal dotted line and the cost function (the shaded area in Figure 8) is the cost saving that would occur as a result of achieving a given level of passive detection probability relative to the base case, and these funds could be used to increase public awareness. For example, in Figure 8, moving from $p_p=0.3$ to $p_p=0.6$ would reduce total cost from \$2.34 million to \$0.99 million; these expected savings of \$1.35 million (in present value terms) could be used to achieve the required gain in passive detections. The vertical distance within the shaded area represents a lower bound on the amount that should be invested in awareness campaigns to achieve a given level of p_p , because the total budget would remain the same as in the base case, but the probability of eradication would increase (as show later) and this has value in terms of reduced damage, which has not been priced in our model.

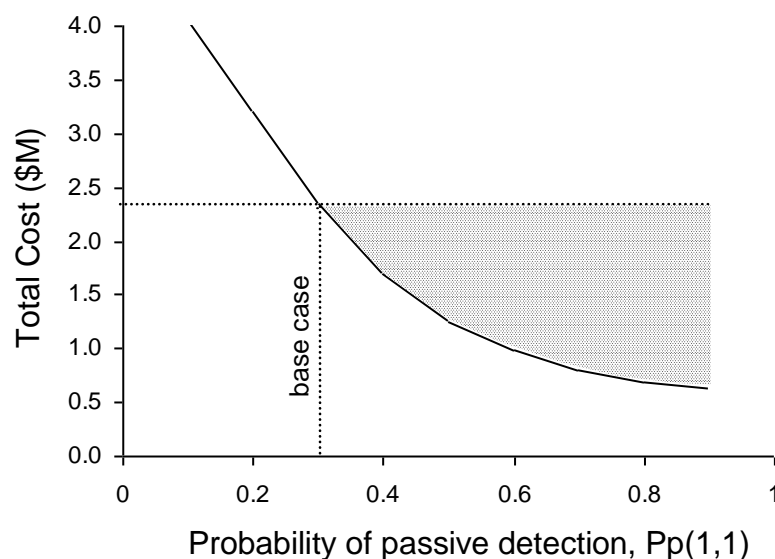


Figure 8. Effect of passive detection probability on total cost of controlling the invasion over 15 years.

The cost-neutral change in the strategy illustrated above may have additional spin-offs. The cost savings of \$1.35 million (in search, control and bounty payments) and investment of these funds in awareness campaigns are likely to underestimate the value of the investment, as public awareness could increase passive detections in public as well as private land, such as when an invasion is found and reported by a person walking in a park, and this possible benefit has not been considered.

4.2 Probability distributions

Cumulative distribution functions (CDF) of final area invaded (Figure 9) provide additional insights. An invasion is defined as being under control when its size is not increasing (i.e. where $X_T \leq X_0$), this is the area to the left of the dotted line in Figure 9. Using this definition, there is a small probability (0.39) that the invasion will be controlled in the base case. It is important to point out that this simplistic definition of control ($X_T \leq X_0$) measures the net area invaded, but gives no indication of the gross area invaded (Rejmanek and Pitcairn, 2002). It is possible that a smaller net area invaded at the end of the simulation could be more scattered across the landscape than the initial invasion, therefore representing a large gross area that is bounded by a larger containment perimeter. In this situation, the invasion is not being truly controlled. Notwithstanding this limitation, $X_T \leq X_0$ is a convenient criterion to eliminate inefficient search strategies.

In Figure 9, as p_p increases from 0.3 to 0.7, control of the invasion is practically guaranteed (the curve labelled *Passive* is entirely to the left of the initial invasion line). This strategy results not only in smaller final invasions, but also in a positive eradication probability (~0.35), given by the intersection of the curve with the vertical axis in Figure 9. In contrast, the base case would not result in eradication, as the curve labelled *Base* intersects the horizontal axis at a positive value (86 ha). In this example active search occurs only in response to passive detections and further detections result in further search, therefore the total search effort represents only follow-up searches and it is not predetermined by the pest-control agency but driven by the search process.

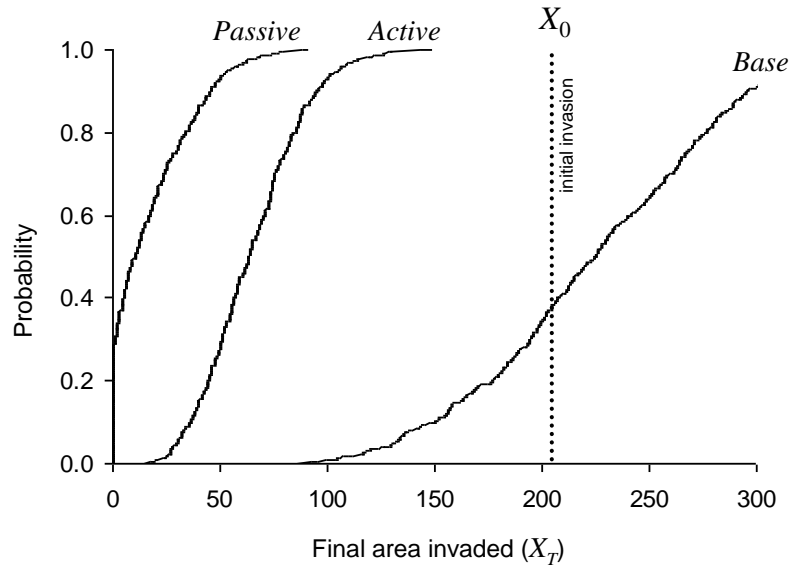


Figure 9. Cumulative distribution functions of final area invaded for the base case (Base), the base case plus active effort (M) of 6554 h (Active), and the base case with passive detection probability of 0.7 (Passive).

Now consider the introduction of independent active search to be allocated randomly in public parcels (Figure 9, curve labelled *Active*). This strategy causes the CDF to shift to the left relative to the base case. Interestingly the left shift is more pronounced on the top portion of the curve, so that the probability of controlling the invasion is enhanced by the active search (the whole *Active* curve is to the left of the initial invasion line), but the probability of eradication is still zero as in the base case (the curve does not intersect the vertical axis).

4.3 Eradication probability

As already established above, the probability of passive detection has a negative effect on the expected final area invaded, $E(X_T)$, but the strength of the effect decreases at a decreasing rate as p_p increases (Figure 10A). In the *Base* case, p_p values > 0.3 achieve control of the invasion (i.e., to the right of point a in Figure 10A $E(X_T) < X_0$) and at p_p values > 0.9 $E(X_T)$ is virtually zero; indicating it is likely that the invasion will be eradicated if passive surveillance can be increased to this level. Introducing active search causes the curve to shift down (dotted line in Figure 10A), indicating a higher likelihood of achieving control of the invasion for any given level of passive detection probability. In this case control is achieved at $p_p > 0.16$ (to the right of point b)

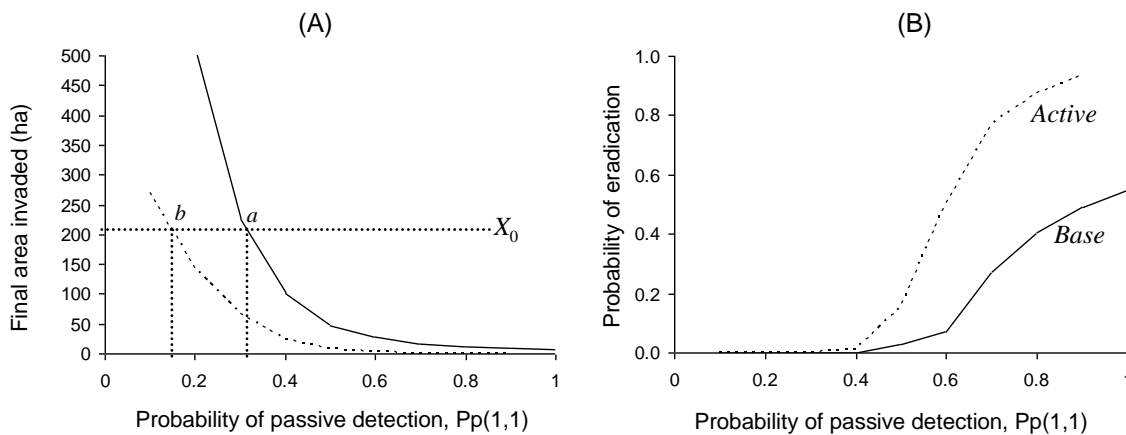


Figure 10. effect of passive detection probability on expected final area invaded (A) and probability of eradication by year 15 (B).

In the *Base* case, the probability of eradication within T years (P_E) becomes positive only when $p_p > 0.5$; reaching $P_E = 0.49$ at $p_p = 0.9$ (Figure 10B). Introducing active search causes an upward shift in the eradication curve, reaching a P_E of 0.93 at $p_p = 0.9$; almost double the probability of eradication achieved with no active search. These results indicate that increasing passive detection in private parcels is a valuable strategy, but there is a limit to its effect on P_E . At some point it is necessary to increase passive surveillance in public areas or introduce active search in such areas to increase the probability of eradication further.

In this section we have identified two measures of performance: probability of eradication (or alternatively the area invaded at any time t) and total cost. The application of these performance measures is further developed in the following section.

5. Economic Efficiency Measures

In the previous section we established the importance of passive surveillance in combination with active search. We also developed a method to determine the minimum amount that should be spent on information campaigns to enhance passive detection probability. In this section we develop further measures of economic efficiency and undertake optimisation analysis to determine desirable strategies in terms of active search allocation.

5.1 Efficient frontiers

The model is designed to simplify the process of analysing the costs and consequences of alternative scenarios. Scenarios are represented as given sets of parameter values. The scenarios in this section differ from each other in terms of passive detection probability (p_p), active search effort available (M) and search effort allocated per cell (m). The model results are expressed in terms of our two performance measures: probability of eradication and total cost (Figure 11).

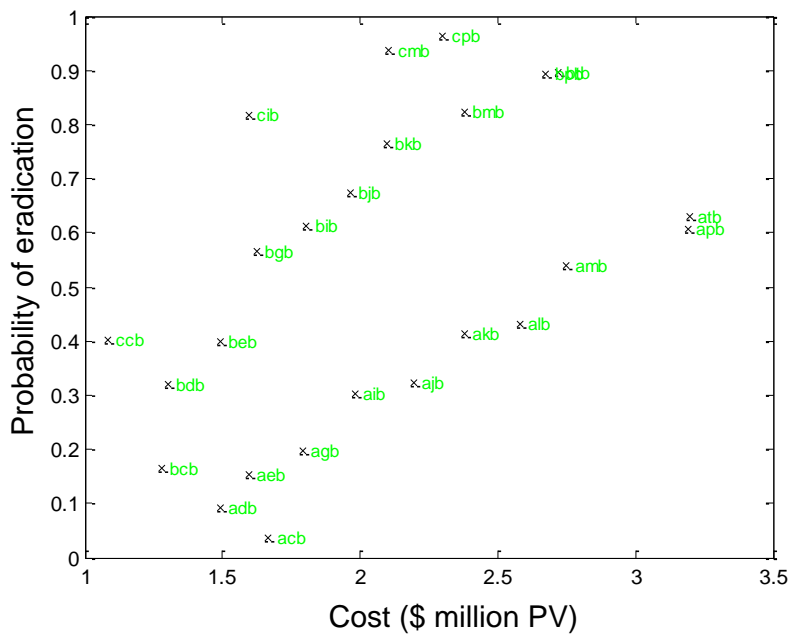


Figure 11. Simulation results for alternative combinations of passive detection probability, active surveillance available and search effort per cell.

In Figure 11 the ideal situation is located at the top left of the plot, where probability of eradication (P_E) is 1.0 and total cost (C) is 0. This leads to a definition of dominance whereby a strategy i dominates strategy j unambiguously ($i > j$) iff:

$$C_i \leq C_j \quad (12a)$$

$$P_{Ei} \geq P_{Ej} \quad (12b)$$

and where the strict inequality applies for at least one of these conditions. Based on this criterion any dominated strategies can be eliminated, leaving an efficient (dominant) set. Graphically, inefficient (dominated) strategies are those occurring below and to the right of another strategy. In Figure 11 the efficient set appears to be (ccb, cib, cmb and cpb) as all other strategies are dominated by one or more in the set. However, recall that the cost of information campaigns to increase passive detection probability (p_p) has not been included;

therefore it is not valid to compare strategies that differ in terms of p_p . Figure 12 presents a subset of results where p_p was maintained at 0.5.

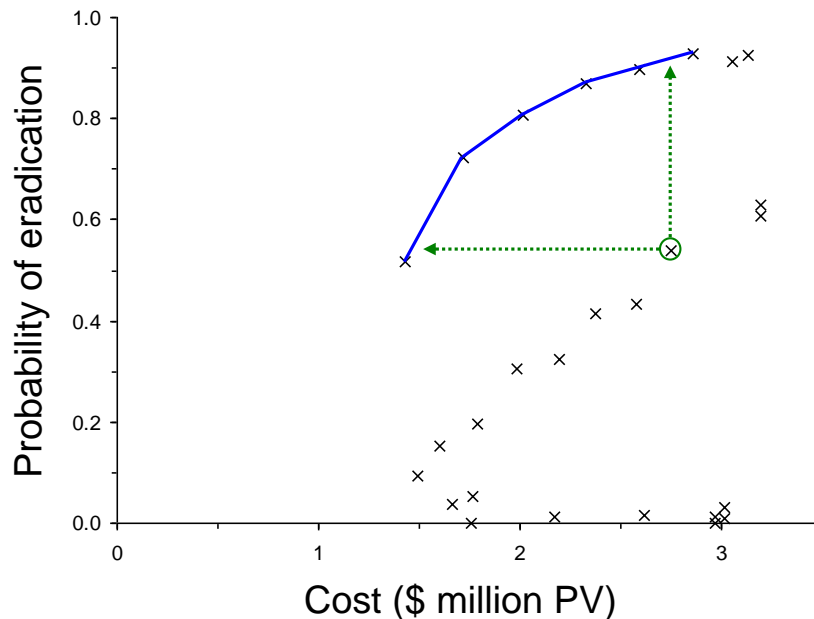


Figure 12. Efficient frontier for a passive detection probability of 0.5 (blue curve), points differ in terms of surveillance available and search effort per cell, green arrows illustrate the range over which the efficient frontier dominates the point circled in green.

The efficient set can be joined to produce what in economics is called an efficient frontier. Any strategies associated with points not on the frontier can be eliminated from further consideration. This is illustrated in Figure 12 by the point enclosed in a circle. This point is inefficient because performance can be improved by moving vertically (up) to the frontier to achieve a higher eradication probability at the same cost, moving horizontally (left) to achieve a lower cost for the same eradication probability, or moving at any angle in between to reduce cost and increase eradication probability. The frontier is sometimes called a trade-off curve and has been used to find efficient land-use patterns when conservation and production are alternative land uses (Groeneveld 2005; Polasky et al. 2005).

The decision of where to operate along the frontier is likely to be determined by a budget constraint. But the budget itself is a policy decision that may be influenced by the perceived value of achieving a given increase in eradication probability. In terms of policy, the preferred point on the frontier may be based on a benefit estimate (i.e. avoided damages) that provides a monetary value for P_E , or on an arbitrary minimum acceptable eradication probability.

An efficient frontier provides a useful policy tool. It can be derived for any given level of passive detection probability and for any given planning horizon, hence enabling agencies to undertake sophisticated policy analyses.

5.2 Optimisation

As explained in the Methodology section, optimisation was undertaken with a genetic algorithm and consisted of finding search strategies that maximised reductions in the size of the invasion at the minimum possible cost. The base-case values reported in Table 1 and the GA parameters in Table 2 were used to initialise the optimisation run (GA). These results

were compared to the *Active* scenario discussed in section 4. In both scenarios a maximum of 6554 hours of active search effort were available to search in public areas each year.

CDF plots of final area invaded provide evidence that the GA produces a considerable improvement over results of the non-optimised, *Active* simulation (Figure 13A). The *Active* strategy did not result in eradication, as the *Active* curve intersects the horizontal axis at a positive value (18 ha) (Figure 13A). In contrast the optimal solution under GA resulted in a relatively high probability (0.61) that the invasion would be eradicated by year 15, and this was achieved at a lower cost than in the *Active* scenario (Figure 13B).

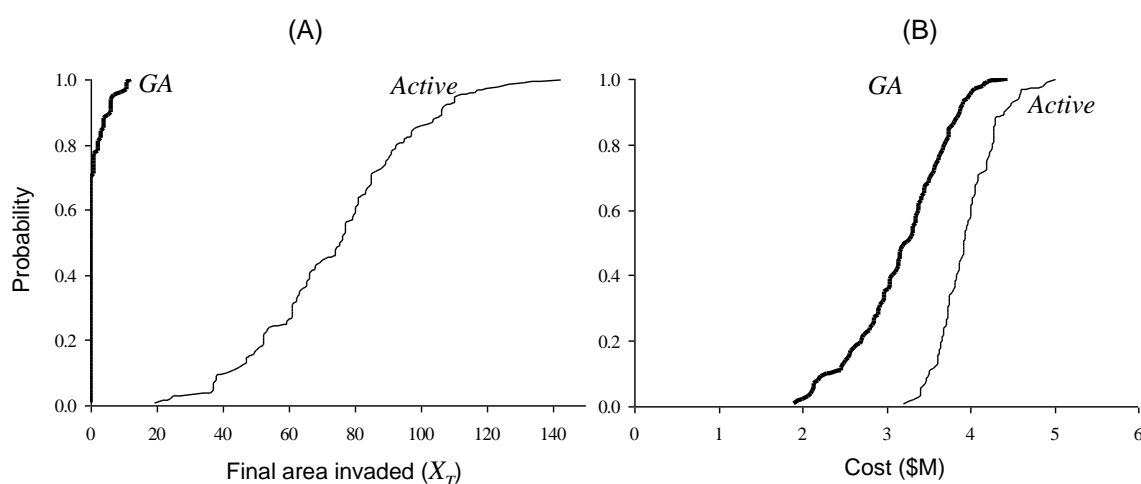


Figure 13. Cumulative distribution functions of final area invaded (A) and Cost (B) showing the base case solution (*Base*) and the optimal solution for the base genetic algorithm (*Base GA*).

The entire cost CDF for *GA* is to the left of the cost CDF for the *Active* case (Figure 13B). These results indicate that the *GA* strategy dominates the base strategy by a considerable margin, in terms of both costs and probability of eradication.

Results in Table 4 indicate that the main difference between the *Active* simulation and the *GA* solution is in the intensity of search per cell (m). In the base case m is 2 hours per cell, compared to 8.06 hours per cell in *GA*. The time spent on active search and following up passive reports is similar for both scenarios, but the effort needed for repeat treatment of infestations in *Active* is more than double that of *GA* reflecting the larger value of S_R in *Active*. Despite a similar passive effort requirement under both scenarios, the actual number of passive finds in *Active* is only around 30% of the *GA* number, indicating that the strategy of a much higher search effort per cell in public lands and in response to a passive find in *GA* pays dividends, with many more finds than is the case in *Active*. As a consequence, the probability of eradication under *GA* is 0.61 and the expected final area invaded is 1 ha, compared to a zero probability of eradicating the infestation and an expected final invasion size of 31 ha under the *Active* scenario.

Other results in Table 4 indicate that the increased search effort per cell (*GA*) should be accompanied by a reduction in the search radius around detections (r_m) from 5 to 4 cells, and repeat visits to previously treated cells (S_R) should occur for only one year rather than three. Using the *GA* strategy the cost of eradication is \$3.19 million, compared to \$3.34 million under *Active*, around a 5% reduction. In both cases most of the cost is attributed to searching for the pest. Although the cost of the bounty payment under both scenarios is small compared to total costs (under 6% of total costs), bounty costs under *Active* are double those of *GA*, again reflecting the effectiveness of the more intense searching that takes place both in

response to passive finds and in public areas under *GA*. The median time to eradication is 13 years under *GA* while it never occurs within the 15-year time frame under *Active*.

Table 4. Comparison between the *Active* scenario from Table 3 and the optimisation results obtained using the genetic algorithm (*GA*). In both cases the passive detection probabilities were set at 0.3 and 0.01 for private and public areas respectively; the active search effort available (*M*) was 6554 h.

	Scenario: <i>Active</i> <i>GA</i>	
<i>Control variables :</i>		
<i>m</i>	2.00	8.06
<i>r_m</i>	5	4
<i>S_R</i>	3	1
<i>Mean results (500 iterations):</i>		
Total cost (\$M)	3.34	3.19
Bounty cost (\$M)	0.16	0.08
Search cost (\$M)	3.17	3.10
Treatment cost (\$M)	0.01	0.01
Final area invaded, $E(X_i)$	31	1
Median year eradicated	--	13
Probability of eradication	0.00	0.61
Mean passive detections (no.)	608	1889
Mean passive effort per year (h)	3,293	3,464
Mean active effort per year (h)	6,427	6,552
Mean repeat effort per year (h)	3,381	1,492

In summary the optimal strategy of a high search intensity, a low number of repeat treatments and a lower search radius for a given probability of passive detection results in earlier and cheaper management of weeds, even if monetary rewards are involved.

6. Potential Applications and Extensions

The models and decision tools we have developed in this project have a number of important potential applications. Some of these applications represent enhancements to the analytical tools available for decision making, others represent contributions to improving the management of specific control programs. These are described briefly in this section.

6.1 Case studies

The parameter values we used in our analysis are all plausible and roughly based on an ant invasion, but they not based on actual data. The next logical step in this research is to apply the model to a specific situation where spatial and temporal data are available to produce maps of habitat suitability, location of known infestations, rural/urban and public/private parcels, and detectability of the invader. Possible candidates for this include the red imported fire ant (RIFA), the European wasp and miconia.

The RIFA (*Solenopsis invicta*) invasion was first recognized in 2001 after being detected near Brisbane's main port. Left untreated, fire ants were estimated to cost \$8.9 billion over 30 years (Kompas and Che, 2001) The Queensland Department of Primary Industries (QDPI) initiated an eradication program in 2001 (Moloney and Vanderwoude, 2003). Since the scheme commenced, the number of nests removed has declined dramatically, from over 65,000 to 90 infested properties in the period July 2007 to April 2008. Most of the recently detected infestations were relatively small, suggesting that infestations are being detected soon after their establishment. However, some of the infestations were far from the original source, suggesting that the invasion is spreading. In April 2008 a bounty scheme was introduced offering a \$500 reward for reports by private citizens of new infestations found before June 23 2008 (QDPIF, 2008). The aim of the scheme was to assist in finding the last remaining ant colonies by encouraging increased reporting and increased searching by private citizens. Payment was made on confirmation of ant presence by QDPI staff. This program offers an interesting case study.

The European wasp (*Vespula germanica*) is an exotic to Australia, and is known to have adverse effects on agriculture, tourism and human health (Widmer et al. 1995). While the European wasp has established in Tasmania, Victoria, South Australia and New South Wales, it has not done so in Western Australia. In that state, wasp nests are destroyed when discovered and the pest has been the subject of an eradication program since 1984. As previously mentioned, the public are responsible for finding 90% of the infestations in new areas (Davis and Wilson, 1991). A complete list of the locations of all known nest sites, the type of nests found, the method by which nests were detected and other relevant information has been compiled for European wasp in Western Australia, making this a good candidate for a case study.

Miconia (*Miconia calvescens*) is a small tree that is native to tropical America and is now an invasive species in the rainforests of the Hawaiian and Tahitian islands, New Caledonia and, more recently, in the wet tropics of Australia. Naturalised infestations were discovered near Kuranda, Queensland, in 1997 with 22 other naturalised populations being recorded by June 2008. A further 23 locations in botanical garden specimens, nursery plants or private garden specimens have been recorded in Australia. Miconia has been a declared weed since 1997 and was included in the 'Four Tropical Weeds' Eradication Program when the program commenced in 2001. Funding for miconia eradication will continue until at least 2012. Miconia offers a promising case study because records of the number of plants killed, the search effort and areas searched have been kept since the inception of the program at many of the invasion locations.

6.2 Generic analysis

Despite the complexity of biological invasions, their essential features can be distilled down to a few parameters that describe rates of spread and growth, habitat suitability, vulnerability to control techniques, and severity of damages caused. Similarly, the essential features of control programs can be distilled down to a few parameters that describe the types and amounts of resources available, the effectiveness and costs of surveillance and control options, and constraints imposed by legislative and environmental restrictions. The development of a typology of invasions in terms of these parameters, and generic analysis for each type of invasion identified, can lead to useful guidelines for rapid response when limited information is available but the general features of an invasion are known. This is an application that could be accomplished at relatively low risk. It will require a well-designed experimental protocol and methodical application of the model to a large number of situations. It will also require a good database strategy to interrogate model results and extract information for statistical analysis. But it could rely mostly on data from the literature and clever design of alternative worlds, rather than requiring detailed input datasets that are difficult to obtain.

For example, Figure 14 shows two different maps of habitat suitability. These maps were generated with the fractal algorithm described in the Methodology section. Both maps have exactly the same frequency distribution of habitat suitability values, but their fractal dimension differs. The map in Figure 14A has weak spatial autocorrelation and results in a more fragmented habitat than the map in Figure 14B. An interesting question is: given two worlds that are identical in all aspects except habitat fragmentation, will optimal management decisions change and if so how? Similar questions can be asked regarding other features of the world such as distribution of urban and rural areas, overlap between land ownership and habitat suitability etc. The advantage of this approach is that we can design experiments and control the variables of interest, something which is not possible for actual managed invasions.

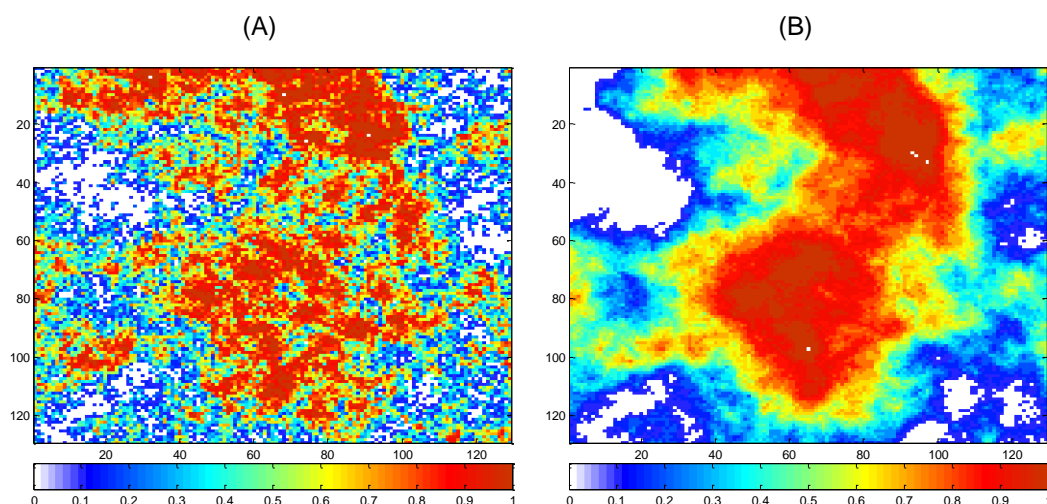


Figure 14. Two alternative habitat suitability maps created with the mid-point displacement algorithm (see Numerical Application in the Methodology section). The maps differ in terms of clustering, controlled by H values of 0.2 (A) and 0.8 (B), but the frequency distribution of habitat suitability values is identical.

6.3 Enhancing passive surveillance

The costs of enhancing passive surveillance are unknown at present, but it should be possible to design studies to measure these costs based on current programs. Increasing detections by the public will ultimately hinge on factors such as (1) the portfolio of media and communication materials used; (2) the severity of the pest (i.e. whether it is a minor nuisance or a serious threat); (3) the receptivity of the public (partly affected by demographic factors such as income, age and education); (4) the simplicity or otherwise of reporting infestations; and (5) the availability of reward schemes.

A bounty scheme can have spin-offs in terms of free media coverage when people who have found infestations and received rewards have interesting stories to tell. Examples of this exist for the RIFA bounty scheme in Brisbane, which has received significant coverage in local newspapers. A bounty scheme may also have negative consequences, such as when people disperse the pest intentionally in order to obtain rewards. Existing data for the RIFA invasion in Brisbane and the European wasp in Western Australia (see section 6.1 above) could be used to develop a behavioural model of passive surveillance.

There is scope for applying mathematical programming techniques to identify efficient portfolios of those factors that are under the control of the agency in charge of an invasion, and to incorporate the constraints placed by the biological, economic and political environments. Principal-agent theory offers interesting prospects. This is essentially a theory of contractual relationships between parties when goal conflict and asymmetry of information exist between the principal and the agent (Waterman, 1998). Principal-agent models have been applied to environmental policy (Moxey et al., 1999; Fraser, 2002), where the principal (the government) sets the mix of monitoring, penalties and rewards to maximise the likelihood that the agents (farmers) will contribute to the goals of agri-environmental programs. To our knowledge, this approach has not been applied to invasive species, but there are interesting opportunities to represent the relationships between biosecurity agencies, the public and pest inspectors. The principal would seek to optimise a bounty scheme by manipulating the probability that the public would assist in the eradication effort while minimising the scope for cheating.

6.4 Optimal search and control strategies

There are important policy decisions which could be studied by manipulating model parameters. For example, treatment effectiveness (p_k) can be manipulated to study the benefits of investing in technology that improves the proportion of treated organisms that are killed. Or the detectability parameter (λ) could be used to test improvements in detection technology, such as the use of dogs to detect fire ants. The benefits and costs of these alternative investments in new technology can then be compared by assessing their effects on eradication probabilities and costs.

The value of information gathered while searching is an added benefit to the immediate benefits from removing organisms. Quantifying such benefits is useful for assisting in the design of integrated surveillance and control programs. For example, it may be more effective to use relatively expensive manual treatment methods that yield information on the distribution and abundance of organisms rather than automated broad-scale treatment methods that do not produce such information. This question can be studied with our model with no need for modification. But more interesting questions can be explored through optimisation.

Our optimisation model is based on a genetic algorithm (GA), a technique that can handle difficult objective functions and problems with high dimensionality, but our particular

implementation is quite basic. Our GA proved valuable for identifying strategies to allocate search effort and reduce costs, but it could be improved considerably by making better use of the probability map generated by the model and by considering what is known about the state of the invasion at any time. This application would require careful thought regarding the representation of the learning process (through evolution of the genetic algorithm) as the invasion progresses.

In terms of deriving rules of thumb, as discussed in the Methodology section, stochastic dynamic programming is a powerful and flexible method of deriving decision rules based on the state of the system at any time, but it is not well suited to spatially-explicit problems. An option is to use the model to derive simplified state variables and design stochastic dynamic programming models for optimisation with respect to the key decision variables. Examples of this approach are provided by Bogich and Shea (2008) and Hyder et al. (2008) among others. The simplified state variables may include total area invaded, average population density and degree of clustering of invasions, for example. The advantage of this approach is that we can derive optimal decision rules that account for future consequences of current actions and is based on the state of the invasion at any time. So we can assess, for example, whether the relative proportion of active and passive surveillance should be adjusted over time depending on whether the invasion is growing.

6.5 Uncertainty analysis

We have accounted for the stochastic nature of dispersal, detection and control of invaders, but we did not account for uncertainty. The nature of the dispersal process and the values of model parameters are important areas of uncertainty. A critical question is under what conditions the presence of uncertainty may change the management and policy decisions that are optimal for a particular type of invasion. From a decision analysis standpoint, uncertainty is important only if it affects our decisions compared to the existing stochastic model. This issue requires some study. Interesting options are offered by methods such as information gap analysis (Reagan et al., 2005; Ben-Haim, 2006) which provides a quantitative measure of the robustness of decisions to severe uncertainty. A similar view of the role of uncertainty in ecological decision models is provided by Burgman et al. (2005) who state that an option to deal with uncertainty is to: “make decisions that maximize the chance of a tolerable outcome, despite what is unknown” (p. 2014).

6.6 Preparedness and Response

Our model can be used to study the tradeoffs and competition for funds between preparedness (pre-discovery) and response (post-discovery). This is an interesting and important question that can be explored by assessing the impacts of time to discovery (t_D) in terms of costs and damages.

Regarding response once the invasion is discovered, our tools could be further developed to identify rapid and efficient methods to delimit and contain the invasion. There is some useful work on this topic reported in the literature (i.e. Mangel et al. 1984) but there is still much work to be done to make the ideas operational and widely applicable.

6.7 Enhancements to the model

6.7.1 Growth

The model is based on presence/absence rather than population density. This has advantages in terms of solution speed, but it imposes some limitations. For example, the number of

propagules produced per infested site are constant in the model. Propagule pressure increases when more sites are infested, but not as the density of the invasion grows within a site, because this increase is not modelled. This is not a problem if the area of the cell is small enough to contain only one or a few individuals, but errors are introduced as the area of the cells increases. Hence, extending the model to include population density per site, rather than considering only presence/absence, will result in a better representation of propagule pressure and will reduce the sensitivity of the model to spatial scale (i.e. reduce the error introduced as the area per cell in the map increases). Population density will also affect the probability of detecting an infested site and this can have important implications for effort allocation.

Another important future enhancement of the model is to introduce a seed bank as an additional state variable. This will allow a more realistic application of our tools to plant invasions, as the presence of a seedbank makes invasions harder to eradicate.

6.7.1 Dispersal

Our model is based on an adjacency matrix, an efficient method to speed up numerical calculations of spatial spread. This approach offers substantial speed advantages over standard methods that rely on applying dispersal kernels to individual infested cells based on Cartesian coordinates. In early tests of our model we achieved 30-fold reductions in the time required to solve some problems by applying an adjacency matrix. This is important because optimisation analysis requires many runs of a model, and thus it can be impossible to apply (within realistic time horizons) to models that require more than a few seconds to complete one run.

The adjacency matrix is a powerful tool and we have only scratched the surface in its application. For example, we assumed that the dispersal kernel applies uniformly in all directions; this implies there are no factors that affect the direction or pattern of dispersal. In our model, the actual dispersal pattern is affected by habitat suitability, which defines the probability of establishment of propagules that land on a cell. So we account for the essential spatial features of the problem, but our approach does not account for factors such as wind, slope and rivers that vary across the landscape and may affect dispersal. These factors can be accommodated with an adjacency matrix by thinking of adjacency not only in terms of proximity but also in terms of connectedness. Developing more detailed adjacency matrices for large maps can be an intensive and complicated effort but, if it improves the feasibility of eradication with a limited budget, investment in such effort may pay off in a short time, particularly for invasions that can cause substantial damages.

6.7.1 User interface

The model is written in the Matlab language, and requires the user to have the software available in their computer. The user does not need to be a Matlab expert, because the model is designed to allow scenarios to be defined within a spreadsheet file (Excel). This file is read by Matlab and the simulation is run. The user generally does not need to access the code, but needs to know how to start a new run in Matlab and how to copy and paste results into Excel. However, some operations require the code to be accessed, for example to change the order in which passive detections, repeat searches and active searches are processed, the user needs to modify one line of code. People who have skills and experience in managing invasions generally do not have access to Matlab and have no interest in manipulating computer code. Hence the importance of developing a user interface and compiling the model into an executable file.

7. Recommendations

1. Apply the model to actual invasions to test its performance and to assist in the design of control plans.
2. Conduct further study on the trade offs and interactions involved in search intensity, passive surveillance and landscape coverage.
3. Study the marginal cost of achieving improvements in passive surveillance and develop a mathematical programming model to identify efficient management portfolios in terms search effort, treatment intensity, information campaigns and reward programs.
4. Introduce uncertainty into the evaluation of alternative surveillance and treatment strategies. Evaluate whether the presence of uncertainty affects the optimal decisions identified with our existing tools.
5. Build upon the optimisation tools developed to devise smarter search strategies; also consider deriving simplified state variables and designing stochastic dynamic programming models for optimisation with respect to the key decision variables and based on the state of the system at any time.
6. Study the tradeoffs and competition for funds between preparedness (pre-discovery) and response (post-discovery). This is an interesting and important question that can be explored in terms of costs, damages and probability of eradication.
7. Extend the model to allow the use of population density as an alternative state variable to absence/presence.
8. Introduce a seed bank as an additional state variable to allow more realistic application of our tools to plant invasions.
9. Further develop the adjacency matrix approach to modelling spatial spread, accounting for factors that affect dispersal such as wind, slope, rivers and roads.
10. Develop a user interface and compile the model into an executable program to be made available to DAFF and other potential users.

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7. Appendix

The operation of the model is as follows.

1. A ‘world’ is created by generating the attribute vectors α , λ , \mathbf{s} , \mathbf{u} , \mathbf{o} , the state vector \mathbf{x} and the adjacency matrix \mathbf{A} .
2. The passive detection probability vector (\mathbf{q}) is created based on attributes \mathbf{u} and \mathbf{o} (equation 7).
3. Other demographic (w , p_L , S_R), economic (δ , C_B , C_m , C_T) and logistic (M , m , p_B , r_m , t_D) parameters are initialised according to the scenario to be tested.
4. An invasion is started at a random location and allowed to spread undetected (applying equations 3 to 5) until the time of discovery t_D . The initial invasion state (\mathbf{x}_t) for $t=1$ is generated (i.e. the time counter starts upon discovery of the invasion).
5. Passive detections are generated by comparing a vector of random numbers (ρ) to the probability of detection of invaded sites ($\mathbf{q} \circ \mathbf{x}_t$). An invasion is detected for cell i if $\rho_i \leq q_i x_{it}$. A proportion p_B of passive detections are reported. The parcels included in the reported set are selected randomly from the passive-detection set.
6. A search area of radius r_m is drawn around each reported cell.
7. Search commences in the areas identified in step 6 by applying the search equation (8) to each cell within these areas; if additional invasions are found these are included in the reported list and step 6 is repeated.
8. Repeat searching of sites previously treated up to S_R years ago is undertaken.
9. When independent searching occurs, a cell is randomly selected from the valid active-search set (initially the entire set of publicly owned cells minus cells already searched in previous steps) and searched by applying effort m .
10. If an invasion is detected in steps 8 or 9, a search area of radius r_m is drawn around each reported cell and searching within this area commences according to equation (8).
11. The amount of active-search effort available and the valid active-search set are updated based on the searches executed in steps 9 and 10. If active-search effort is still available, steps 9 to 11 are repeated. Otherwise step 12 is executed.
12. Control is applied to all cells where invasions were detected; these invasions are eliminated with probability p_k . The state of the invasion \mathbf{x}_t is updated.
13. The time counter is increased. If $t < T$, the invasion spreads (applying equations 3 to 6) and the state of the invasion \mathbf{x}_t is updated. If $t=T$, results are saved, the time counter is restarted and the simulation returns to step 4 for the desired number of Monte Carlo iterations.
14. Results from simulations are converted to cumulative distribution functions (CDFs) and relevant summary statistics are calculated.