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Optimal allocation of resources to emergency response actions for invasive species
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Summary

This study creates a simple general model for pest surveillance that minimises expected surveillance and management costs.

First, it identifies how much surveillance effort is justified economically by weighing cost against the expected benefits of early detection.

Second, it determines how to allocate a limited surveillance budget over space to minimise expected management costs.

The approach is demonstrated using data for orange hawkweed (*Hieracium aurantiacum*) in alpine Victoria, Australia. However the method is sufficiently flexible for use in a range of terrestrial and marine environments, where natural features and/or economically valuable species are threatened by pest species.

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Disclaimer

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Executive Summary

Habitat suitability maps can be constructed and used to target pest surveillance to locations where the pest is most likely to occur. However, the varying environmental attributes and land uses in a landscape may affect more than just the probability of pest occurrence. Biodiversity or economic value, and the ease of pest detection and control are also likely to vary. To incorporate these factors, we build a simple general model of pest detection and management to determine the surveillance strategy that minimises expected surveillance and management costs. First, we identify how much surveillance effort is economically justified by weighing its cost against the expected benefits of early detection. Second, we determine how to allocate a limited surveillance budget over space to minimise expected management costs. Sites with a high probability of pest occurrence and great benefits associated with early detection warrant intensive surveillance; however the level of surveillance is a nonlinear function of these factors. Sites where the pest will be relatively easy to detect are prioritised for surveillance, though only a moderate amount of effort may be necessary to guarantee a high probability of detection. Intensive surveillance effort may be allocated to other sites if the probability of pest occurrence and the budget or economic returns are sufficiently high. This approach to allocation of surveillance resources is demonstrated using data and models of orange hawkweed (*Hieracium aurantiacum*) in alpine Victoria, Australia. However the method is sufficiently flexible for use in a range of terrestrial and marine environments, where natural features and/or economically valuable species are threatened by pest species.

Introduction

Invasive pest species cost billions of dollars to agriculture annually as well as altering biodiversity via predation, competition or habitat alteration (Pimental *et al.* 2000, 2005, Mack *et al.* 2005, Sinden *et al.* 2005). This has yielded an extensive literature on the prevention of entry, eradication, control, and impact mitigation of such species. Many studies employ an economic framework to advise the best approach, trading off the costs of implementing pest management against the damages that the pest inflicts on the environment (Pandey and Medd 1991, Sharov and Liebhold 1998, Wu 2001, Eisworth and Johnson 2002, Eiswerth and van Kooten 2002, Leung *et al.* 2002, Olson and Roy 2002, Sharov 2004, Odom *et al.* 2005, Cacho *et al.* 2008).

The most effective approach to pest management at any time typically depends on the abundance and/or distribution of the species. Such information can rarely be obtained quickly, cheaply or completely. Fewer studies have considered the effects of imperfect detection on pest management (Brown *et al* 2004, Cacho *et al.* 2006). In particular, only a small number of studies have explicitly incorporated the costs and benefits of monitoring pest species into an economic framework of pest management. Sharov (2004) calculated a sample intensity that minimises the cost of pest treatment, independent of the damages caused by a pest. Regan *et al* (2006) and Rout, Salomon and McCarthy (unpublished data) determined the optimal duration of post-control monitoring at a site by trading the costs of such monitoring against the potential costs of prematurely declaring eradication. Mehta *et al.* (2007) identified the level of search effort that minimises the expected total costs of monitoring, control and damage for a newly introduced pest species. Prattley *et al.* (2007) used portfolio theory to find robust allocations of monitoring resources in space and time for the detection of disease in animals; however they did not model the process of imperfect detection while monitoring is applied.

These studies outline the conditions under which the collection of information on pest presence or abundance is justified, yet the spatial heterogeneity of pest distribution over a landscape has not yet been fully addressed (though Prattley *et al*. 2007 use semi-quantitative methods to model differential risk). Studies by Buchan and Padilla (2000), Underwood *et al.* (2004), Inglis *et al.* (2006) and Williams *et al.* (2008) provide species-specific models that predict the probability of pest presence as a function of environmental variables. The resulting maps are intended to assist in the targeting of monitoring and control resources to areas that have mostly likely been invaded.

We take this approach further by setting it within an economic framework. When we seek to minimise the costs of surveillance and incursion management, the resource allocation to each point in space should not depend only on the probability of pest occurrence provided by a habitat suitability index. It should also be influenced by the ease of detection in the local environment, and the costs of detecting and failing to detect the pest where it occurs. We determine the best allocation of resources across a heterogeneous landscape, both with and without a budget constraint. We illustrate our method with surveillance of orange hawkweed (*Hieracium aurantiacum*) in south-eastern Australia.

The Model

We divide the landscape that the pest could potentially inhabit into *n* sites of equal area. Site boundaries are chosen so that within a site, there is a uniform probability that the pest is present and a uniform probability of detecting the pest using the available surveillance methods. For example, sites might represent different vegetation types across a landscape, fields with different crops and other land uses, or marine areas with different depths.

The probability that the pest is present at site *i* is denoted p_i. It can be estimated using any information available relating to the pest or the site, e.g., host density; environmental characteristics that indicate its suitability for the pest; a history of pest presence; distance from known incursions.

The probability of detecting the pest, conditional on its presence, depends on the ease of pest detection using the available surveillance methods, given the terrain. For example, it may be more difficult to detect a weed in a site with shrubby vegetation than a site with open vegetation. In addition, the probability of detecting a pest where it is present depends on the amount of effort or resources expended. As surveillance effort increases, the probability that an incursion remains undetected declines.

We use a Poisson model to calculate the probability of detecting the pest. This comes with the assumption that the spatial distribution of the pest within the site is random. Parameter $\square_i$ defines the underlying efficacy of the surveillance method at site *i*, per dollar spent on surveillance. The total monetary allocation to surveillance at site *i* is denoted x_i. Thus, the probability of failing to detect a pest incursion at site *i* after x_i was spent on surveillance, is

$\exp(-\square_i \, x_i)$.

Conversely, the probability of successfully detecting the pest when it is present is

$1 - \exp(-\square_i \, x_i)$.

We assume that where the pest is absent, it is never erroneously detected.

At sites where the pest is detected, we assume that actions are triggered to locally eradicate the pest. This may include methods of destruction or removal, as well as follow-up monitoring of the infested area to confirm eradication. Such procedures incur staffing and equipment costs. There may also be losses associated with the confirmed pest presence, from damage to biological integrity through to lost revenue from agriculture. We use c_i^D to represent the combined costs associated with detecting the pest at site *i*.

If the pest is present but not detected at a site it has the capacity to spread to other sites, causing further damage and becoming more difficult to eradicate. We use c_i^U to denote the cost of having an undetected pest at a site, and assume that it is larger than c_i^D.

Minimising the costs of surveillance and management

In the absence of budget restrictions, there exists a trade-off between the cost of surveillance and the cost of managing pest incursions. At each site *i*, the expected combined costs of surveillance and incursion management are

(1) $$T_i(x_i) = x_i + p_i \left\{ c_i^D \left[1 - \exp\left(-\lambda_i x_i\right) \right] + c_i^U \exp\left(-\lambda_i x_i\right) \right\}.$$

The expected combined costs at site *i* therefore depend on the surveillance expenditure x_i. While the cost of the chosen surveillance allocation is always incurred, the expected cost of incursion management varies depending on the surveillance strategy and the distribution of the pest. If the pest is absent there are no incursion costs, and so the cost of incursion management is weighted by the probability of pest presence p_i. If the pest is present, the incursion could be detected (with probability $1 - \exp(-\lambda_i x_i)$) and incur costs c_i^D or left undetected (with probability $\exp(-\lambda_i x_i)$) and incur costs c_i^U .

We find the surveillance expenditure x_i^* that minimises the combined expected costs of surveillance and incursion management by partially differentiating the cost function (equation 1) with respect to x_i and setting the result to zero:

(2) $$\frac{\partial T_i}{\partial x_i} = 1 - p_i \lambda_i \left(c_i^U - c_i^D \right) \exp(-\lambda_i x_i^*) = 0.$$

Rearrangement of this equation gives

(3) $$x_i^* = \frac{\ln\left[\left(c_i^U - c_i^D \right) p_i \lambda_i \right]}{\lambda_i}.$$

However, this solution is only meaningful if $x_i^* \geq 0$. This holds true if and only if

(4) $$p_i \left(c_i^U - c_i^D \right) \geq \frac{1}{\lambda_i}.$$

The term $p_i \left(c_i^U - c_i^D \right)$ can be interpreted as the expected savings made by determining the status of the site, while $1/\lambda_i$ is the mean surveillance expenditure required to detect the pest at the site, given that the pest is present and surveillance ceases on detection. If this condition (4) does not hold, then the cost of surveillance overwhelms the benefits it is expected to provide and the surveillance allocation that minimises costs is $x_i^* = 0$. This may occur because the pest is unlikely to be at the site (p_i is small), the surveillance method is ineffective per dollar spent at the site (λ_i is small), or early detection of the pest offers few benefits ($c_i^U - c_i^D$ is small).

Thus, the surveillance allocation x_i^* that minimises expected costs of surveillance and incursion management at site *i* is

(5) $$x_i^* = \begin{cases} \dfrac{\ln\left[(c_i^U - c_i^D) p_i \lambda_i\right]}{\lambda_i}, & p_i\left(c_i^U - c_i^D\right) > \dfrac{1}{\lambda_i} \\ 0, & p_i\left(c_i^U - c_i^D\right) \le \dfrac{1}{\lambda_i} \end{cases}$$

When $p_i(c_i^U - c_i^D) > 1/\lambda_i$, there is a positive amount of surveillance effort that optimises the trade-off between surveillance costs and incursion management costs. The higher the probability of pest presence at a site, the more surveillance effort should be allocated (Fig 1a). Note however that the relationship in equation 5 is logarithmic rather than directly proportional. Similarly, as the benefits from early incursion detection ($c_i^U - c_i^D$) increase, so does the optimal surveillance effort (Fig 1a). This again is a logarithmic relationship.

The effect of surveillance efficacy on the optimal surveillance effort at a site is more complicated (Fig 1b). A highly ineffective surveillance method should not be used at all, while a moderately effective method warrants a high allocation of effort at a site. When a surveillance method is highly effective, less effort is required at the site because detection is almost certain given only moderate effort. Further marginal increases in detection probability (which are declining exponentially) are not large enough to justify the additional surveillance expenditure.

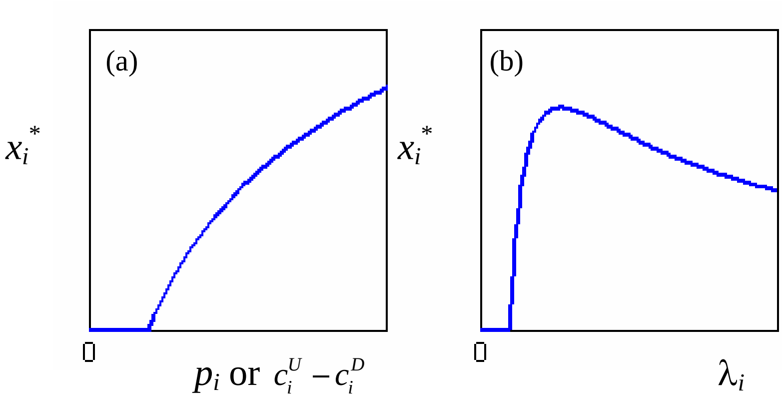


Figure 1. Optimal surveillance effort as a function of (a) probability of pest presence p_i and benefits accrued from early detection ($c_i^U - c_i^D$), and (b) surveillance efficacy λ_i.

Allocating surveillance effort subject to a budget

In many circumstances the resources available for surveillance will be limited. If the resources available for monitoring are less than those required for the optimal solution in section 3, then we are faced with distributing monitoring resources amongst the sites. We denote the surveillance budget as *B*, and add the constraint that

$$\sum_{i=1}^{n} x_i \le B.$$

We determine how to distribute this budget *B* across sites to minimise the total expected cost of incursion management:

$$(6)\qquad \begin{aligned} T(\mathbf{x}) &= \sum_{i=1}^{n} p_i \left\{ c_i^D \left[1-\exp(-\lambda_i x_i)\right] + c_i^U \exp(-\lambda_i x_i) \right\} \\ &= \sum_{i=1}^{n} p_i c_i^D + \sum_{i=1}^{n} \left(c_i^U - c_i^D\right) p_i \exp(-\lambda_i x_i) \end{aligned}$$

which is the expected cost of incursion management for a site (given in equation 1) summed over all sites $i = 1, 2, \ldots, n$. The second expression of this cost divides it into two parts. The first part is the unavoidable control cost incurred when all incursions of the pest are detected (averaged over the possible number of infested sites). The second part is the additional control cost incurred by a failure to detect one or more incursions, given the surveillance allocation: $\mathbf{x} = \{x_1, x_2, \ldots, x_n\}$.

Our control over the system is limited to altering the surveillance allocation $\mathbf{x}$, so minimising $T(\mathbf{x})$ is equivalent to minimising

$$(7)\qquad U(\mathbf{x}) = \sum_{i=1}^{n} \left(c_i^U - c_i^D\right) p_i \exp(-\lambda_i x_i).$$

(i) Graphical method

The benefit of allocating surveillance effort to each site can be observed by plotting their contributions to the sum $U(\mathbf{x})$ individually, as a function of surveillance effort (Fig 2):

$$U_i(x_i) = \left(c_i^U - c_i^D\right) p_i \exp(-\lambda_i x_i).$$

We call this the expected control impact at site *i* given that x_i is spent on surveillance. This impact declines as surveillance effort increases but the absolute reduction made by each additional dollar spent on surveillance diminishes. That is, the gradient of $U_i(x_i)$ determines the efficiency of investing in further surveillance at site *i*, given that x_i dollars have already been allocated to the site:

$$U_i'(x_i) = -\left(c_i^U - c_i^D\right) p_i \lambda_i \exp(-\lambda_i x_i).$$

Thus, the first site to be prioritised for surveillance is the site with the steepest gradient at $x_i = 0$ in the graph (site 2, Fig 2). As money is allocated to the site we move along the x_i axis and investment efficiency declines. There may now be another site that offers equivalent improvements for each dollar spent on surveillance, and funds are allocated to both sites. This procedure continues, with further sites receiving surveillance funding, until the budget *B* is exhausted.

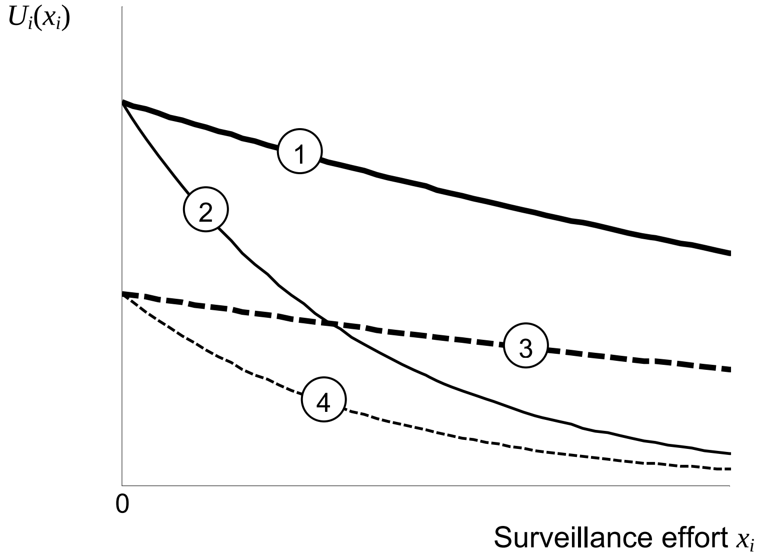


Figure 2. The expected control impact of the pest U_i as a function of surveillance expenditure x_i at each of four sites: (1) high expected control impact and low surveillance efficacy; (2) high expected control impact and high surveillance efficacy; (3) low expected control impact and low surveillance efficacy; and (4) low expected control impact and high surveillance efficacy.

(ii) Numerical method

The graphical method is an intuitive approach to allocating a surveillance budget when there are a relatively small number of sites in the landscape. However, the optimal allocation of surveillance resources can be formalised using the Kuhn-Tucker conditions for nonlinear optimisation under inequality constraints (Léonard & Long 1992; p. 52-56).

We introduce a function □ and parameter □ such that

$$\phi(\mathbf{x}, \mu) = -\sum_{i=1}^{n} \left(c_i^U - c_i^D \right) p_i \exp(-\lambda_i x_i) + \mu \left(B - \sum_{i=1}^{n} x_i \right).$$

Then by the Kuhn-Tucker conditions, any optimal solution **x** must satisfy:

$$\frac{\partial \phi}{\partial \mu} \geq 0, \mu \geq 0, \text{ and } \mu \frac{\partial \phi}{\partial \mu} = 0,$$

$$\frac{\partial \phi}{\partial x_i} \leq 0, x_i \geq 0, \text{ and } x_i \frac{\partial \phi}{\partial x_i} = 0 \text{ for } i = 1, 2, ..., n.$$

Now

$$\frac{\partial \phi}{\partial \mu} = B - \sum_{i=1}^{n} x_i \geq 0, \mu \geq 0, \text{ and } \mu \frac{\partial \phi}{\partial \mu} = \mu \left(B - \sum_{i=1}^{n} x_i \right) = 0.$$

Since every increase in surveillance expenditure x_i improves the objective function $U(\mathbf{x})$, then the entire budget must be exhausted. Thus,

(8) $$\sum_{i=1}^{n} x_i = B \text{ and } \mu > 0.$$

Furthermore,

$$\frac{\partial \phi}{\partial x_i} = (c_i^U - c_i^D) p_i \lambda_i \exp(-\lambda_i x_i) - \mu \leq 0, x_i \geq 0,$$

and

(9) $$x_i \frac{\partial \phi}{\partial x_i} = x_i \left[(c_i^U - c_i^D) p_i \lambda_i \exp(-\lambda_i x_i) - \mu \right] = 0 \text{ for } i = 1, 2, ..., n.$$

Some sites may be allocated zero surveillance funding, while others are allocated a positive number of dollars. As shown during the development of the graphical method, sites can be prioritised according to the efficiency of investing surveillance in them i.e. the gradient of $U_i(x_i)$. Note that before any surveillance is allocated, the efficiency at any site i is $U_i'(0) = -\left(c_i^U - c_i^D\right) p_i \lambda_i$. With this motivation, we relabel sites 1, 2, …, n in descending order of $\left(c_i^U - c_i^D\right) p_i \lambda_i$. If any sites have equal efficiency, then the site with higher surveillance efficacy λ_i is numbered first. This sets a priority list of where each initial unit of surveillance effort will provide the greatest reduction in impact. Similar to the situation where the budget was not constrained, sites that are not allocated any surveillance have an acceptably low probability of pest presence (p_i), low additional control costs when undetected ($c_i^U - c_i^D$), or the surveillance method is not sufficiently effective at that site (λ_i is low).

Then there exists some k between 1 and n (inclusive) so that sites i = 1, 2, …, k are allocated positive surveillance effort, while sites i = k+1, k+2, …, n receive no surveillance. Then from equation 9

(10) $$x_i^* = \begin{cases} \dfrac{1}{\lambda_i} \ln\left[\dfrac{(c_i^U - c_i^D) p_i \lambda_i}{\mu} \right], & i = 1, 2, ..., k \\ 0, & i = k+1, k+2, ..., n. \end{cases}$$

Substituting equation 10 into the budget equation 8 gives

$$\sum_{i=1}^{k} \frac{1}{\lambda_i} \ln\left[\frac{(c_i^U - c_i^D) p_i \lambda_i}{\mu} \right] = B,$$

which can be rearranged to show that

$$\ln \mu = \frac{\sum_{i=1}^{k} \lambda_i^{-1} \ln\left[(c_i^U - c_i^D) p_i \lambda_i \right] - B}{\sum_{i=1}^{k} \lambda_i^{-1}}.$$

We define

(11) $$\bar{\lambda}(k) = \frac{k}{\sum_{i=1}^{k} \lambda_i^{-1}} \text{ and } \bar{x}(k) = \frac{1}{k} \sum_{i=1}^{k} \frac{\ln\left[(c_i^U - c_i^D) p_i \lambda_i \right]}{\lambda_i}.$$

Then $\bar{\lambda}(k)$ is the harmonic mean of the {□$_i$}, or the average surveillance efficacy. The arithmetic mean $\bar{x}(k)$ is the average unconstrained-optimal allocation across sites 1 to *k*.

Now the optimal allocation in equation 10 must be

(12) $$x_i^* = \begin{cases} \dfrac{\ln\left[(c_i^U - c_i^D) p_i \lambda_i \right]}{\lambda_i} + \dfrac{\bar{\lambda}(k)}{\lambda_i} \left[\dfrac{B}{k} - \bar{x}(k) \right], & i = 1, 2, \ldots, k \\ 0, & i = k+1, k+2, \ldots, n. \end{cases}$$

The form of the solution is similar to the unconstrained problem (equation 5), but the allocation to each site is moderated by the budget *B* and the efficiency of investment at this site *i* relative to the other sites 1 to *k*. The term *B*/*k* is the funding that each site would be allocated if surveillance dollars were allocated equally to all sites and $\bar{x}(k)$ is the average funding we would hope to allocate to each site if we were not constrained by the budget. Thus, the difference between them will be negative when the budget falls short of the ideal surveillance expenditure, and the surveillance allocated to the site will be reduced from the ideal unlimited-resource level. Multiplying by $\bar{\lambda}(k) / \lambda_i$ tailors this reduction according to the efficacy of surveillance at the particular site *i* relative to the other sites. Thus, sites where surveillance is highly effective will not have their allocation of funding reduced as substantially as those where surveillance is ineffective.

To ensure that surveillance effort at sites *i* = 1, 2, …, *k* are indeed positive, we must have

$$\ln\left[(c_i^U - c_i^D) p_i \lambda_i \right] > \bar{\lambda}(k) \left[\bar{x}(k) - \frac{B}{k} \right] \text{ for all } i = 1, 2, \ldots, k.$$

Since the sites are indexed in descending order of $\left(c_i^U - c_i^D\right) p_i \lambda_i$, this condition reduces to

(13) $$\ln\left[(c_k^U - c_k^D) p_k \lambda_k \right] > \bar{\lambda}(k) \left[\bar{x}(k) - \frac{B}{k} \right].$$

The total expected control impact will then be

(14)
$$\begin{aligned} U(\mathbf{x}^*) &= \sum_{i=1}^{n} (c_i^U - c_i^D) p_i \exp(-\lambda_i x_i^*) \\ &= \frac{k}{\bar{\lambda}(k)} \exp\left(-\bar{\lambda}(k) \left[\frac{B}{k} - \bar{x}(k) \right] \right) + \sum_{i=k+1}^{n} (c_i^U - c_i^D) p_i . \end{aligned}$$

The actual number of sites *k* that are allocated positive surveillance funding is still unknown. To find the optimal allocation of funding amongst *n* sites subject to a budget, we:

1. Label sites 1, 2, …, *n* so that the sites are in descending order of efficiency $\left(c_i^U - c_i^D\right) p_i \lambda_i$. If any sites have equal efficiency, then the site with higher surveillance efficacy □*i* is numbered first.
2. Calculate $\bar{\lambda}(k)$ and $\bar{x}(k)$ for each possible *k* = 1, 2, …, *n* using equation 11;
3. Refine the set of possible *k* by rejecting those that violate condition 13;
4. Calculate the objective function *U* (equation 14) for the remaining plausible *k* and select k^* where it is minimised;
5. Substitute k^* into equation 12 to find the optimal allocation.

Rather than examining the 2^n combinations of site inclusion and exclusion from the set of surveyed sites, this approach reduces the number of candidate solutions that must be examined to *n*.

Case study: surveillance for orange hawkweed on the Bogong High Plains, Australia

Orange hawkweed (*Hieracium aurantiacum*) is a daisy with a distinctive orange flower. It is native to Europe, but has become a weed in the United States, Canada, Australia and New Zealand. It is thought to have been deliberately introduced to the Bogong High Plains Unit of the Victorian Alpine National Park in the 1980s, though it was first recorded as naturalised only in 1999. Since then it has been found at two other widely separated locations in alpine south-eastern Australia. Although its distribution is currently limited, it poses a substantial threat to Australian agriculture and to the conservation value of the Alpine National Park if left unmanaged. Thus, orange hawkweed has been declared as a nationally and state prohibited weed, and the local population is subject to seasonal survey, mapping and herbicide spraying with the aim of eradication (Williams and Holland 2007).

To assist in the targeting of surveys for new infestations, Williams et al. (2008) constructed a dispersal-constrained habitat suitability model for orange hawkweed across the Bogong High Plains. The model predicts the probability of hawkweed presence at each location on a 20 m-resolution grid as a function of the level of disturbance, site wetness, vegetation community, and probability of wind dispersal from known infestations. Observer time available to survey for new infestations is limited, and we demonstrate how our method of surveillance allocation can inform the management of orange hawkweed on the Bogong High Plains.

To divide the Bogong High Plains into a manageable number of equal-sized sites, we used resampling techniques to create 4250 sites of dimension 200m x 200m. Associated with each site was a predicted probability of orange hawkweed occurrence (p_i) and the site's vegetation community. It was thought that the local vegetation community would influence an observer's ability to detect orange hawkweed. Thus, the 15 vegetation communities used for the dispersal-constrained habitat suitability model were re-categorised as either 'low grassy' or 'shrubby'. In consultation with a local expert on hawkweed surveillance (N.S.G. Williams, *personal correspondence*) we developed models of the probability of detection as a function of time spent at a site (Fig 3), yielding surveillance efficacy estimates □ = 0.3283 $\$^{-1}$ for low grassy vegetation and □ = 0.0834 $\$^{-1}$ for shrubby vegetation. These models assumed that the detection surveys were carried out in summer when orange hawkweed flowers. Detection probabilities would be much lower if the species was not flowering.

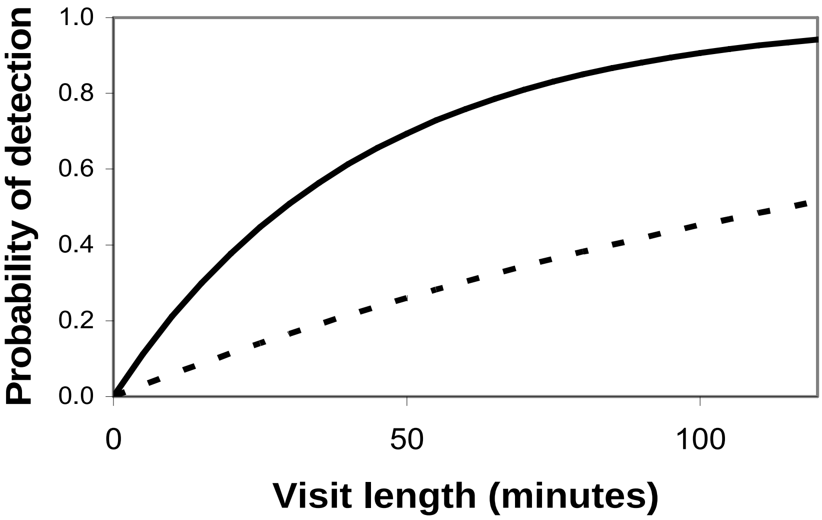


Figure 3. The probability of detecting orange hawkweed at a 4 ha site, given it is present. The probability is a function of the time spent at the site, and whether the site contains low grassy (solid line) or shrubby (dotted line) vegetation.

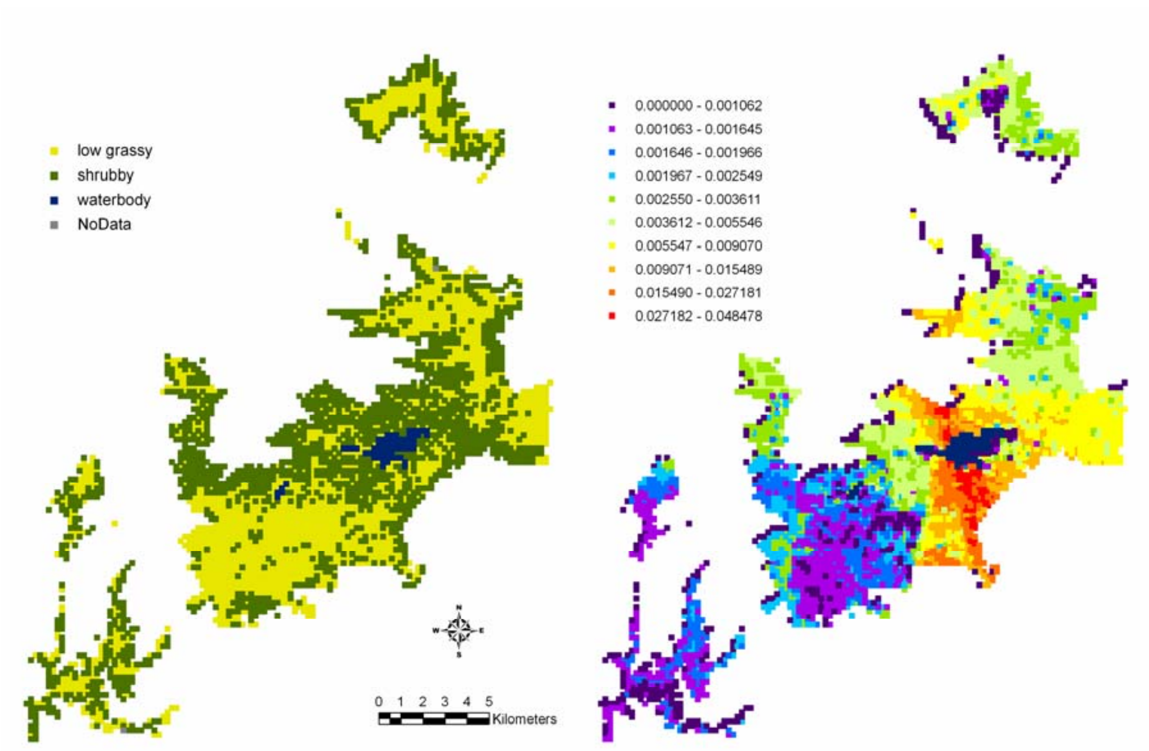
We assume that the costs of monitoring and spraying known hawkweed infestations do not vary from site to site. Known sites of infestation are visited weekly during the peak hawkweed season. Seeds may survive for up to seven years, and so this monitoring must continue over multiple seasons to confirm eradication at the site. We estimate this cost of hawkweed management when it is detected to be $c_i^D = \$1000$. The ultimate cost of managing hawkweed if it is not successfully detected and contained to a site this season (c_i^U) is more difficult to estimate, and we present results assuming $c_i^U = 100c_i^D$. During the 2007/2008 season, roughly $20000 was spent employing two people to search the Bogong High Plains for new infestations. In addition, multiple volunteers contributed to the search effort. These efforts equated to a total of approximately 1125 hours of search time.

We determined the optimal surveillance allocations under our model using a simple spreadsheet. The total cost of surveillance under the budget-unconstrained allocation is $264000 or 15230 person hours, well beyond the current budget. Figure 4 shows the modelled vegetation type, probability of orange hawkweed presence, and optimal surveillance allocation for the Bogong High Plains in the absence of a budget. While 7.0% of sites receive no surveillance at all, the few most high risk shrubby sites are to be visited for almost 13 person hours. This reflects both the relatively high probability of orange hawkweed presence (5%) and the difficulty of detecting the plant in this vegetation type.

The effect of the variable surveillance efficacy can also be observed in the far eastern region on the maps. While the probability of orange hawkweed occurrence is relatively uniform around 0.005-0.01 (Fig 4b), the optimal surveillance allocation varies substantially (Fig 4c), particularly as a response to vegetation type (Fig 4a). Even though more survey time is recommended for a shrubby site than a site with low grassy vegetation and the same probability of hawkweed presence (Fig 5), the probability of detection is still lower (Fig 6). The probability of detection under the optimal surveillance allocation is a non-decreasing function of the probability of pest presence p_i, the benefits gained from early detection ($c_i^U - c_i^D$), and the surveillance efficacy $\square_i$.

As the available surveillance budget increases, more sites are included in the surveillance plan, and each site receives more effort (Fig 5). It is also possible to plot $U(\mathbf{x}^*)$, the total expected control impact under the optimal allocation, for a range of budgets (Fig 7). This could assist in deciding what budget to set for the surveillance of a pest, basing the decision on the expected incursion management savings to be made. Note that for budgets greater than the budget-unconstrained solution (B = $264000), the expected costs of incursion management continue to decrease. However the savings made to incursion management are less than the additional expenditure on surveillance.

Finally, consider the case where we do not have the dispersal-constrained habitat suitability model created by Williams et al. (2008). If we were to distribute effort uniformly across the Bogong High Plains, spending 16 minutes at each site, the total expected control impact would be almost $1.7 million. By comparison, the expected control impact using the optimal allocation is about $1.3 million. Thus, the benefit of an accurate dispersal-constrained habitat suitability model could be valued at $375,000.



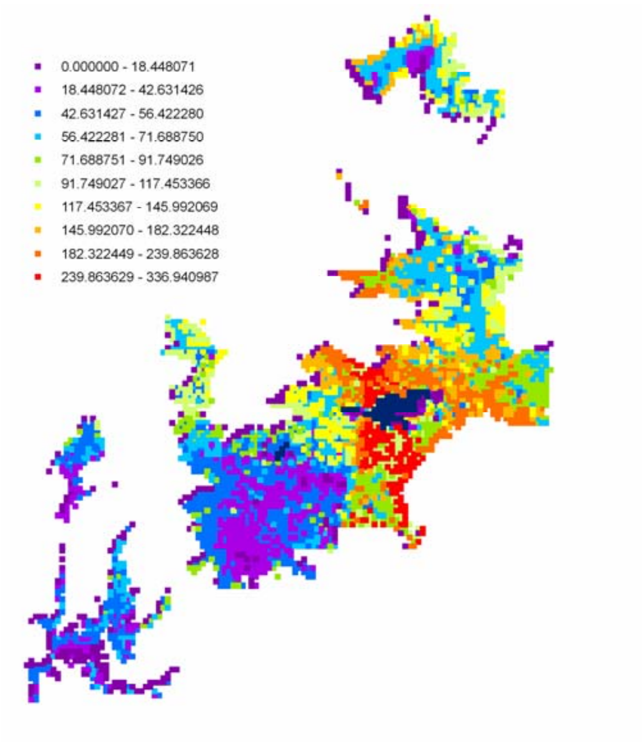


Figure 4. (a) Vegetation type, (b) probability of orange hawkweed occurrence (Williams *et al.* 2008), and (c) optimal allocation of surveillance dollars over the Bogong High Plains. The optimal allocation is for the budget-unconstrained problem with $c_i^U = 100 c_i^D$.

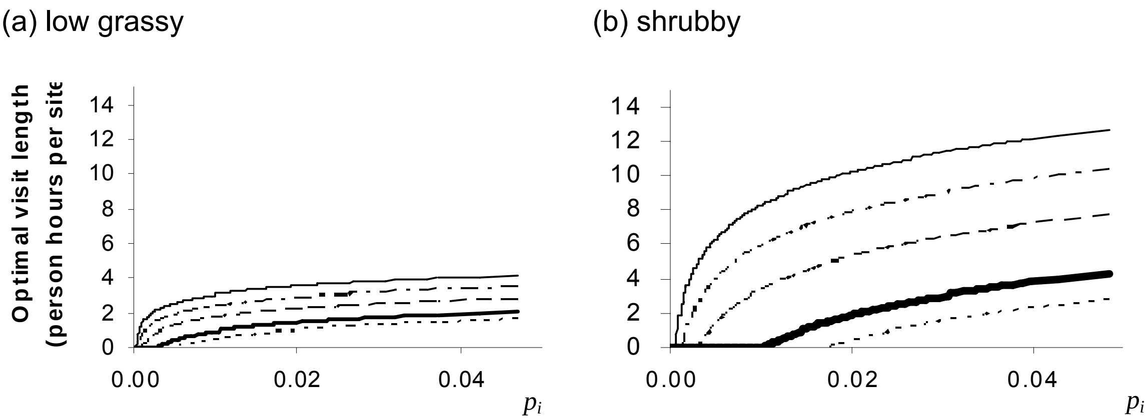


Figure 5. Optimal budget-constrained allocation of survey hours to each site, as a function of the probability of orange hawkweed occurrence at the site. Vegetation is (a) low grassy, or (b) shrubby. The total budgeted survey hours are 500 (dotted line), 1125 (the current budget, thick solid line), 5000 (dashed line), 10000 (dot-dashed line) and 15000 (thin solid line).

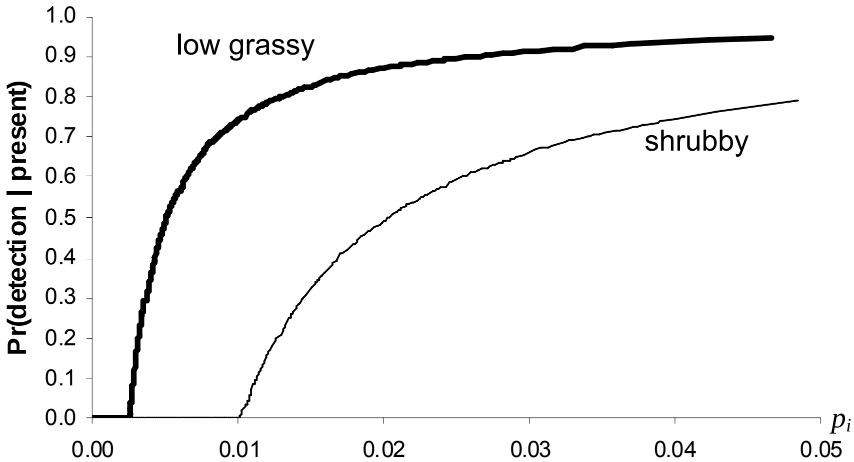


Figure 6. The probability of detecting orange hawkweed at a site where it is present, as a function of the probability of orange hawkweed occurrence at the site. The optimal allocation of surveillance resources under the current budget of 1125 person hours is assumed.

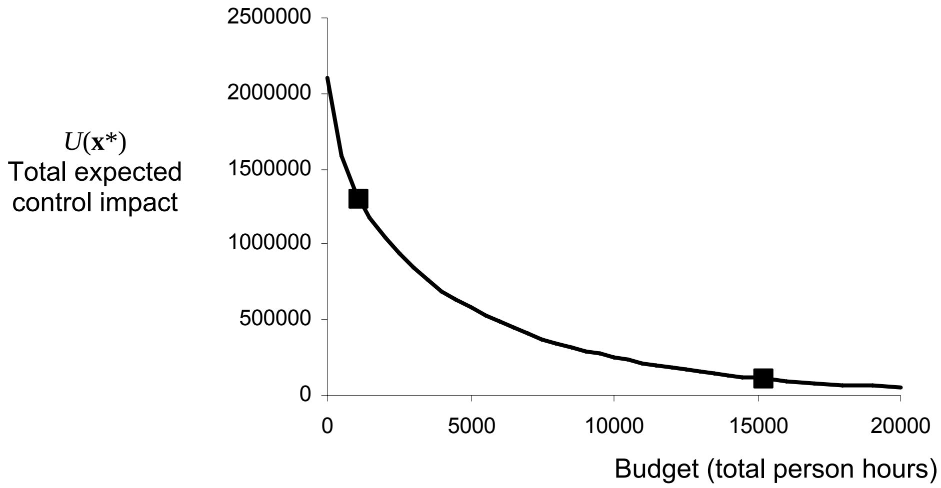


Figure 7. The total expected control impact $U(\mathbf{x}^*)$ (in dollars) under the optimal surveillance allocation, as a function of budget. Squares indicate the current budget of 1125 person hours, and the unconstrained-optimal solution where 15230 person hours are used.

Discussion

There has been some interest in modelling the probability of pest occurrence to help prioritise surveillance effort over space (Buchan and Padilla 2000, Underwood *et al.* 2004, Inglis *et al.* 2006, Williams *et al.* 2008). However, these studies have not demonstrated the optimal relationship between the probability of occurrence and variable surveillance effort. We have shown that this relationship is logarithmic, so that allocation increases at a diminishing rate as the probability of occurrence increases. It is interesting that the mathematical formulation and solution of the problem of allocating effort among areas of threat is identical to the problem of allocating conservation reserves among bioregions to protect endemic species (McCarthy et al. 2006).

Less attention has been paid to how differences in the probability of pest detection across a heterogeneous landscape should influence surveillance effort. Our case study demonstrates the importance of differing detection rates for surveillance prioritisation. While the eastern region in Fig 4 has a relatively uniform (and medium level) probability of hawkweed occurrence, the optimal visit length varies according to the vegetation type. Sites with shrubby vegetation are allocated greater funds to ensure a thorough search in difficult terrain. In general, sites where the pest will be relatively easy to detect are prioritised for surveillance, though only a moderate amount of effort may be necessary. Intensive surveillance effort may be allocated to other sites if the probability of pest occurrence and the budget or economic returns are sufficiently high.

The specific benefits of early detection will also influence both the optimal total expenditure on surveillance and its allocation across space. The difference between the costs of incursion management with and without early detection, $c_i^U - c_i^D$, exerts influence in the same manner as the probability of pest presence p_i; sites where early detection offers great benefits should receive more surveillance, albeit at a decreasing rate (Fig 1a). In the case study we assumed that this benefit would be the same at all sites, but this may not be the case. Some sites may be considered more valuable than others in some sense, or more susceptible to damage. In these cases our method can accommodate this information and prioritise accordingly.

Furthermore, attaching an economic value to the impact of a pest may be difficult or inadequate when a pest threatens a landscape valued primarily for its biodiversity rather than an economic return. In these cases the budget-constrained formulation may still be of use, with the term $c_i^U - c_i^D$ being replaced by some other measure of the relative value of different sites. Otherwise, contingent valuation or other non-market valuation methods might be used to assess the value of protecting areas from invasive species. Market-based estimates would be available when an invasive species threatens agricultural production.

It should be noted that the detection rates and probabilities of occurrence modelled here rely on expert opinion and parameters of similar systems taken from the literature (Williams *et al.* 2008). It is likely that parameters will not be known with confidence and so there is a need to test a surveillance allocation for robustness, rather than relying solely on the optimal allocation derived from point estimates. We have briefly explored the sensitivity of this solution to the costs of failing to detect the pest, but further research is warranted.

As we begin to incorporate uncertainty in parameter estimates and perhaps model structure, the model can be updated with new information as surveillance progresses. For example, we may alter our habitat suitability map as subsequent pest detections and apparent absences alter our understanding of where the pest is likely to occur. A fully active adaptive surveillance and management plan would require a more dynamic model, explicitly incorporating likely dispersal over time and the results of surveillance.

As it stands, we are able to make some inferences on the value of information. At the end of the case study we compared the expected costs under the optimal surveillance allocation to those incurred when applying uniform surveillance effort across the landscape, as if there were no information about the varying habitat and corresponding likelihood of pest presence. In this way we may be able to estimate the value to future management of discerning differences in habitat before a habitat model is developed.

Prioritisation of pest management efforts across species, space and time is an increasingly important task. We demonstrate that in prioritising efforts across space for a single species, we should be concerned with more than just the probability of pest presence at each location. Both the value of early detection and the relative ability of our surveillance method to detect the pest in the local environment should also influence how much we spend on surveillance and where we direct it.

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