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Adaptive management improves decisions about where to search for invasive species

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A B S T R A C T

Invasive species managers must decide how best to allocate surveillance and control effort through space. Doing this requires the predicted location of the invasive species, and these predictions come with uncertainty. While optimal surveillance designs have been developed for many invasive species, few have considered uncertainty in species distribution and abundance. Adaptive management has long been recommended for managing natural systems under uncertainty, but has not yet been applied to searching for invasive species. We investigate whether an adaptive management approach can increase the number of individuals found and removed, as compared to a naïve allocation of search effort or "common sense" rules of thumb. We develop a simple illustrative model where search effort must be allocated to maximise plant removals across two sites in which species abundance is unknown. We tested the performance of both passive and active adaptive strategies through simulation. There are substantial benefits to employing an adaptive strategy, although the two forms of adaptive management performed similarly. The optimal active adaptive strategy is complex to calculate, whereas the passive strategy could be calculated for a large number of sites using widely accessible spreadsheet software. We therefore recommend the passive adaptive strategy for achieving approximately the same outcome while being much more practical to implement, facilitating application to much larger and more realistic search problems in a way that is accessible to managers.

1. Introduction

A primary concern for invasive species managers is how best to allocate surveillance and control effort through space (Chadès et al., 2011; Epanchin-Niell et al., 2012; Hauser and McCarthy, 2009; Regan et al., 2011). Achieving this requires the predicted location of the invasive species, now and/or in the future. Expert opinion (Williams et al., 2008), species distribution models that correlate occurrence with environmental attributes (Elith et al., 2010; Guisan et al., 2013), or other spatial population and spread models (Adams et al., 2015; Caplat et al., 2012; Coutts et al., 2011; Gallien et al., 2010) can provide these predictions.

However these predictions are made, they will come with some uncertainty. Expert judgements can be biased, although bias can be minimised by using structured elicitation processes (Martin et al., 2012; Sutherland and Burgman, 2015). Predictive models are simplifications that will imperfectly represent biological relationships (Levins, 1966). In addition, imperfect detection means that occupancy or abundance cannot be known perfectly, even if a landscape were comprehensively surveyed (Chen et al., 2013; Garrard et al., 2008; MacKenzie and Kendall, 2002; Moore et al., 2011; Royle et al., 2005). If we ignore this uncertainty and treat our point predictions as the true species distribution, our survey designs may be suboptimal. This increases the risk of missing infestations where they occur, and applying excessive effort where they do not.

While optimal surveillance designs have been developed for a wide range of species invasions, few consider uncertainty in species distribution and abundance. Methods for optimally allocating search effort generally assume that occurrence probabilities are accurately predicted by models (Chadès et al., 2011; Hauser and McCarthy, 2009; Regan et al., 2011) or species abundance is uniform across the landscape (Epanchin-Niell et al., 2012; Rout et al., 2014; Rout et al., 2011). Alternatively, search effort can be allocated to maximise the probability of achieving an acceptable outcome in the face of uncertainty (McCarthy et al., 2010). None of these approaches aim to reduce uncertainty about abundance in different locations. A notable exception is

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Baxter and Possingham (2011), who modelled the Receiver Operating Characteristic curve of an uncertain distribution map and calculated the trade-off between searching for the species and reducing uncertainty in the distribution map. They found that under long management time frames, initial investment in learning about species distribution increased the likelihood of eradication. Acknowledging and planning for uncertainty in distribution and abundance when designing surveys can, therefore, improve invasive species management outcomes.

Adaptive management is a solution to the problem of managing systems under uncertainty (Parma et al., 1998). This approach to management not only acknowledges uncertainty and its effect on decision-making, but also seizes opportunities to reduce this uncertainty (Walters, 1986). The two types of adaptive management, passive and active, both use the information learned through management to improve future decision-making. Active adaptive management involves planning ahead for future learning opportunities, and may involve decisions that sacrifice current management performance in return for information that will improve management performance in the future (Williams, 2001). In contrast, passive adaptive management takes the best action at each time point given the current state of knowledge, updating that knowledge after the results of the action are observed.

Optimal adaptive management theory has been applied to harvesting of fish (Walters, 1981; Walters et al., 1993; Walters and Hilborn, 1976) and waterfowl (Nichols et al., 1995; Williams and Johnson, 1995), vegetation restoration (McCarthy and Possingham, 2007), reintroduction (McCarthy et al., 2012; Rout et al., 2009), metapopulation management (Southwell et al., 2016), and threatened species management (Chadès et al., 2012; Moore and Conroy, 2006). While it is potentially useful for invasive species management (Shea et al., 2002), there have been no applications thus far.

This paper investigates whether adaptive management is a useful approach for spatially allocating search and management effort for invasive species under uncertainty. We outline a simple illustrative problem of allocating effort between two sites of uncertain habitat suitability for a species, with the aim of finding and removing as many individuals as possible. Searching a site not only finds individuals, but also increases confidence in estimates of total abundance at that site, which should in turn improve future allocation decisions. Although searching for invasive plants usually occurs across a much greater number of sites, condensing this to the simplest two-site problem is necessary to find the optimal active adaptive management strategy. We investigate the extent to which active and passive adaptive management approaches can increase the number of individuals found and removed, as compared to a naïve allocation or common sense rules of thumb. We then discuss the implications for landscape-scale search and removal of invasive plants.

2. Material and methods

2.1. Optimisation framework

We considered two sites to be surveyed for a plant population. Across a series of T surveys, a searcher aims to find as many plants as possible. However, the abundance of plants in each site i is unknown, and could be between 0 and $N_i^{\max}$ individuals. We developed an optimisation model to find the best way to allocate search effort between the two sites.

Each survey ($t = 1, \ldots, T$) has a budget of effort B_t to be allocated between the sites. The decision variable is the amount of effort allocated to site 1 ($x_{1,t}$), with the remainder allocated to site 2 ($x_{2,t}$). The effort allocated to site i will determine the probability of detecting each individual in that site:

$$p_{i,t} = 1 - e^{-\lambda_i x_{i,t}}, \tag{1}$$

where λ_i is the detection rate at site i. The probability of detection is the same for each individual in a site, and is independent of the detection (or non-detection) of other individuals in space and time. This exponential detection-effort curve is based on predictions from search theory (Frost and Stone, 1998), assuming that individuals are distributed throughout the sites and are encountered randomly. (If individuals are clustered, detection rates can increase with abundance (McCarthy et al., 2013)). This functional form is supported by the few studies that have measured the detection-effort relationship in the field (Chen et al., 2009; Garrard et al., 2008; Moore et al., 2011).

We assume that surveys are carried out close enough in time that there is no reproduction or mortality; thus only the detection and removal of individuals affects the plant abundance in each site. The number of plants newly found in site i during survey t ($c_{i,t}$) can be used to estimate the number of plants in each site before surveys began ($N_{i,0}$). The number of undetected individuals remaining after survey t ($N_{i,t}$) can then be estimated from the estimate of $N_{i,0}$ and the number of individuals found. Found individuals are marked and/or removed and thus do not contribute to detections in future surveys.

Before surveys begin, we assume that our prior belief regarding plant abundance at site i follows the distribution:

$$\Pr(N_{i,0} = n \mid \alpha_i, \beta_i) = \frac{\binom{\alpha_i + n}{\alpha_i} e^{-\lambda_i \beta_i n}}{\sum_{k=0}^{N_i^{\max}} \binom{\alpha_i + k}{\alpha_i} e^{-\lambda_i \beta_i k}}$$
$$\text{for } n = 0, 1, 2, \ldots, N_i^{\max}, \tag{2}$$

where parameters α_i and β_i determine the shape of the distribution. Parameter $\alpha_i \geq 0$ is a counting number and is measured on the same scale as plant abundance; it is indicative of the distribution's centre of mass. Parameter $\beta_i \geq 0$ is any positive real number and is measured on the scale of search effort. When $\alpha_i = \beta_i = 0$ we recover a discrete uniform distribution over $n = 0, 1, 2, \ldots, N_i^{\max}$.

We can update our understanding of plant abundance after each survey using effort data ($x_{i,j}$, $j = 1, 2, \ldots, t$), detection data ($c_{i,j}$, $j = 1, 2, \ldots, t$) and Bayes' theorem. At any time t, the number of plants detected $c_{i,t}$ is drawn from a binomial distribution with probability of success $p_{i,t}$ (Eq. (1)) and number of trials $N_{i,0} - \sum_{j=1}^{t-1} c_{i,j}$ (i.e. the number of plants not yet detected and removed from the site).

We find that after survey t, the posterior probability distribution for the initial plant abundance in site i is given by:

$$\Pr(N_{i,0} = n \mid \alpha_i, \beta_i, C_{i,t}, X_{i,t}) = \frac{\binom{\alpha_i + n}{\alpha_i + C_{i,t}} e^{-\lambda_i(\beta_i + X_{i,t})n}}{\sum_{k=C_{i,t}}^{N_i^{\max}} \binom{\alpha_i + k}{\alpha_i + C_{i,t}} e^{-\lambda_i(\beta_i + X_{i,t})k}}$$
$$\text{for } n = C_{i,t}, C_{i,t} + 1, C_{i,t} + 2, \ldots, N_i^{\max}, \tag{3}$$

where $C_{i,t} = \sum_{j=1}^{t} c_{i,j}$ is the total number of plants found in site i across the first t surveys, and $X_{i,t} = \sum_{j=1}^{t} x_{i,j}$ is the total time spent searching site i (see Appendix A for derivation). The probability distribution for the number of undetected plants remaining in site i after survey t is then:

$$\Pr(N_{i,t} = n \mid \alpha_i, \beta_i, C_{i,t}, X_{i,t}) = \frac{\binom{\alpha_i + C_{i,t} + n}{\alpha_i + C_{i,t}} e^{-\lambda_i(\beta_i + X_{i,t})n}}{\sum_{k=0}^{N_i^{\max} - C_{i,t}} \binom{\alpha_i + C_{i,t} + k}{\alpha_i + C_{i,t}} e^{-\lambda_i(\beta_i + X_{i,t})k}}$$
$$\text{for } n = 0, 1, 2, \ldots, N_i^{\max} - C_{i,t} \tag{4}$$

(see Appendix A for derivation). We can then calculate the expected number of undetected plants remaining in site i after survey t as:

$$E(N_{i,t} \mid \alpha_i, \beta_i, C_{i,t}, X_{i,t}) = \sum_{n=0}^{N_i^{\max} - C_{i,t}} n \Pr(N_{i,t} = n \mid \alpha_i, \beta_i, C_{i,t}, X_{i,t}). \tag{5}$$

Passive adaptive management aims to maximise expected performance given current levels of uncertainty, while active adaptive management aims to maximise long-term performance while acknowledging changes in uncertainty. Active adaptive management can therefore involve sacrificing short-term performance to gain