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Optimizing invasive species control across space: willow invasion management in the Australian Alps

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Summary

1. A key problem facing invasive species management is how best to allocate surveillance and control effort. Models of the establishment and spread of invasive species are widely used to predict species' occurrence across space and inform resource prioritization. However, the way they should be used to direct control effort is less clear. Managers could exhaustively search and treat the few highest priority locations or apply less thorough effort more broadly. The choice between these options is a question of balancing resources to maximize local success while minimizing further spread.

2. We link a spatial model predicting the likelihood of occurrence with a decision model to efficiently allocate human resources to control the weed *Salix cinerea* in south-eastern Australia. Using data collected during an ongoing control programme, we construct a species distribution model, empirically estimate control effectiveness and perform a budget-constrained optimization that identifies priority regions for control.

3. Two alternative scenarios were explored against two seasonal budgets: control is equally valued in all areas or control is doubly valuable in conservation areas.

4. Optimal control effort per site varied according to the likelihood of occurrence and site-specific benefits of control. Prioritizing conservation areas led to a reduction in area treated because of greater allocation of control effort.

5. Quantifying control effectiveness was critical for realistically allocating control effort. Targeting obvious individuals and then moving to new sites was more cost-effective than attempting to control every individual at a high-priority site.

6. *Synthesis and applications.* We have developed a method to identify priority locations for invasive species control across a landscape. By integrating a decision model with an empirical distribution model, our method offers a better management outcome by maximizing the efficiency of control efforts. It identifies where and how much control effort should be allocated for maximum effect within a season. Effort is expressed as control staff time spent per site with the allocation readily visualized as a map. In general, a strategy of visiting sites where the species is most likely to occur and exerting a moderate amount of effort at these sites is most efficient.

Key-words: alpine, control effort, decision theory, detection rates, landscape scale, optimization, *Salix cinerea*, species distribution model, weed management

Introduction

The strategic allocation of surveillance and control effort across the landscape is a primary objective in invasive species

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management. Recent advances in invasive species management include population and metapopulation models for predicting rates and patterns of spatial spread (Auld & Coote 1980; Moody & Mack 1988; Higgins, Richardson & Cowling 1996; Wadsworth *et al.* 2000; Buckley *et al.* 2005) and species distribution models that can be used to direct surveillance and intervention efforts to areas where the species is most likely to be (Mau-Crimmins, Schussman & Geiger 2006; Steiner *et al.* 2008; Williams, Hahs & Morgan 2008). Some approaches combine distribution models with population or spread models to identify locations of high-priority source populations (Brown, Spector & Wu 2008; Fox *et al.* 2009).

These methods successfully identify those regions where the species is most likely to occur. However, the methods do not take into account other factors that may affect the optimal allocation of resources available for control efforts throughout the landscape. For example, the ability to detect and control the target species may also be affected by habitat type or other environmental factors not correlated with species occurrence. Furthermore, we may attach a different value (economic, biodiversity or social) to protecting different areas and their associated environmental attributes from an invading species. The cost of implementing surveillance and control may also vary spatially. To maximize our efficiency, multiple factors must be considered simultaneously.

Spatially explicit modelling is computationally intensive, and thus, many studies have relied upon simulation modelling to draw conclusions (Menz, Coote & Auld 1980; Higgins, Richardson & Cowling 2000; Wadsworth *et al.* 2000; Grevstad 2005). More recently, Burnett, Kaiser & Roumasset (2007), Hyder, Leung & Miao (2008) and Blackwood, Hastings & Costello (2010) have applied optimization methods to spatially explicit models of invasive species control. Hauser & McCarthy (2009) addressed spatial variation in costs and benefits for invasive species surveillance. They determined the allocation of survey effort across a landscape that minimizes the total expected cost of controlling an invasion. Their method prioritizes sites for surveillance using spatially explicit information on the probability of species occurrence, detectability and the benefits of successful detection and control. A key component of the model is the relationship between survey effort and the probability of detecting the species if it is present. Sites with a high probability of species occurrence, which have high value and where the species is moderately hard to detect, warrant the highest survey effort. Although the value of control and its spatial variation were modelled, a manager's ability to regulate the intensity of treatment effort was not addressed.

In this study, we adapt Hauser & McCarthy's (2009) spatial surveillance prioritization model to allocate control effort for an invasive weed based on the predicted distribution of the weed and empirical estimates of control effectiveness. While Hauser & McCarthy modelled the relationship between survey effort and species detection, we focus on identifying the optimal allocation of control effort that encompasses both the search and treatment phases and estimate its effect on future species occurrence. We envisage a situation where control staff are sent out to find and treat weeds in one process. The weed occurs in moderate densities but there is substantial uncertainty about its location. Hence, the control process integrates effort spent searching and effort applied to treating the individuals when they are identified. We call the combined activity of finding and treating individuals as 'control'.

We apply the model to the management of a highly invasive willow *Salix cinerea* L. throughout the Bogong High Plains region of the Alpine National Park in south-eastern Australia. The species has large and expanding populations in the surrounding valleys with seed known to disperse tens of kilometres (Cremer 1999); it is therefore feasible that any area of suitable habitat within the region could be colonized by the species. The aim is to allocate time and resources to minimize the overall likelihood of occurrence across the study area over the course of one control season (5 months). To achieve this, we (i) identify the areas at greatest risk of *S. cinerea* invasion by creating a predictive distribution model as a function of environmental suitability and disturbance; (ii) account for previous control efforts that have reduced the likelihood of *S. cinerea* occurrence in some parts of the park; (iii) validate the model using independently collected field data; (iv) estimate control effectiveness; and (v) apply an optimization model to identify priority regions for control.

Materials and methods

STUDY SPECIES AND REGION

Salix cinerea is an invasive dioecious Eurasian shrub willow (ARMCANZ 2000). It is the only willow to have invaded Australia's relatively weed-free alpine and subalpine regions (McDougall *et al.* 2005), and although restricted to moist environments, it is not limited to riparian areas. Reproducing predominantly by seed, a light pappus facilitates long-distance seed dispersal (Cremer 1999, 2001; Pautasso 2009), allowing the rapid colonization of disparate areas. No persistent seed bank is formed in Australia (Cremer 1999). A ready colonizer of disturbed environments, the species is also able to regenerate after fire (Karrenberg, Edwards & Kollmann 2002).

The Bogong High Plains (1500–1884 m) is one of the Australia's largest contiguous alpine and subalpine areas comprising approximately 18 000 ha of alpine and subalpine grassland, heathland, wet heathland, bog and snow gum *Eucalyptus pauciflora* Sieber ex Spreng. woodland. Annual precipitation varies between 1200 and 2400 mm, falling as snow above 1400 m for 3 months of the year (Costin *et al.* 2000; Williams, Wahren & Ashton 2008). In 2003, a severe wildfire burnt the majority of the Bogong High Plains, baring wet sediments that were previously heavily vegetated by bog and wet heath communities. In these newly exposed substrates, mass germination of *S. cinerea* seedlings occurred. The invasion on the Bogong High Plains is concentrated in the nationally threatened bog and wet heath vegetation communities (DEWHA 2009). The efficient detection and removal of this invader are therefore a high priority for the National Park management.

There are more than 1800 ha of mapped bogs and other suitable habitat but the annual control budget is sufficient to search only a small portion of this area. Hence, the seasonal problem faced by management is to decide which areas to target first and how much area can realistically be treated given the limited budget. Will the overall occurrence of willows be reduced if selected areas are controlled exhaustively or if more areas are controlled less thoroughly? The most effective strategy may require control to be less than 100% thorough at all sites. The adoption of such a strategy may avoid the managers' past tendency to focus on doing a thorough job in a few locations and thereby neglecting to visit others.

DISTRIBUTION MODEL

We used modelling software Maxent (Phillips, Anderson & Schapire 2006) to estimate the potential distribution of *S. cinerea*. Maxent uses a maximum entropy approach to fit species distribution models to presence-only data and environmental variables for defining suitable habitat. The technique is gaining popularity for estimating the distribution of suitable habitat for invasive species (Brown, Spector & Wu 2008; Rodder & Lotters 2008) where the use of absence data is often inappropriate as populations are not likely to be at equilibrium (Welk 2004; Pearson 2007). As *S. cinerea* is a relatively recent addition to the flora of the Bogong High Plains, it is unlikely that all suitable habitat has been occupied.

Species data

The park management agency provided 591 presence records; 5 years of eradication activities (458 records) were supplemented with observations from studies of willow dynamics and bog condition (133 records). These records identify locations where *S. cinerea* seedlings, juveniles and the occasional mature individual were found prior to treatment. The data set was randomly subsampled to one presence per 100 m grid to minimize spatial autocorrelation (549 records).

Environmental variables

Twelve environmental variables were used for modelling. Six variables were derived from a 20-m digital elevation model using terrain analysis software in ArcMap 9·2 (ESRI 2006): altitude, slope, aspect, annual solar radiation (Fu & Rich 2000), topographic position (within a 200-m window) and a steady-state topographic wetness index (Moore, Grayson & Ladson 1993). Six other variables were also used: geological substrate (Morand *et al.* 2005), radiometric soil data U, Th and K (GADDS 2008), vegetation class (DSE 2004), and the spatial distribution of fire severity for the 2003 wildfire and a smaller wildfire from 2007, which re-burnt the north-western region of the park (DSE 2003; Lau *et al.* 2007). The data for these six variables were provided as spatially continuous GIS layers and converted to 20-m grid format. The entire landscape was composed of 458 342 of these grid cells, a resolution that facilitated the best characterization of the heterogeneous environment.

Model fitting

We used Maxent 3·2·28 with all environmental variables and default settings to fit the model. Presence records were randomly partitioned 70:30 into training and testing categories (Fielding & Bell 1997). The stability of model predictions was evaluated by 100 cross-validations from which the average and standard deviation of model predictions were calculated. We report the mean relative suitability, a logistic output scaled to express the likelihood of the species' occurrence at a site based on the site's environmental conditions, and assuming a uniform sampling effort was used to collect all presence records (Phillips & Dudik 2008). Predictive accuracy was assessed with the area under the ROC curve (AUC), which for presence-only data quantify the ability of the model to discriminate between a suitable and a randomly selected site (Phillips, Anderson & Schapire 2006). The AUC statistic was interpreted according to the guidelines suggested by Hosmer & Lemeshow (2000): a score of 0·7–0·8 acceptable, a score of 0·8–0·9 excellent and a score > 0·9 outstanding.

Previous control effort

Control effort over the period 2003–2008 altered willow distribution; therefore, we modified the suitability-based predictions to account for past control efforts. Control effort was estimated as the number of summers that willow control had taken place within each grid cell (20 m) based on GPS records. The likelihood of occurrence was then modified in proportion to the amount of control undertaken. We assumed that control effort applied to a cell in any given year resulted in treatment of a set proportion, p, of the individuals present and that this treatment level could be represented by a proportion reduction in the likelihood of occurrence. Hence, if site i has been treated n times, the likelihood of occurrence, y_i, is calculated as:

$$y_i = (1 - p)^n x_i \qquad \text{eqn 1}$$

where x_i is the suitability index produced using Maxent. We estimated mean proportion treated, p, as 0·65 (±0·11) using the data collected to estimate control effectiveness in 2007–2008.

Distribution model validation

Validation of model predictions was assessed using an independent presence–absence data set of 141 samples (19 presences and 122 absences) collected in 2008–2009. Accuracy was assessed with the AUC statistic. Survey plots were selected using stratified sampling across three vegetation and two wetness strata (in proportion to frequency of strata) from three distinct regions of the Bogong High Plains using ArcMap 9·2 (ESRI 2006) and Hawth's Tools (Beyer 2004). Survey plots were circular with a radius of 10 m and had a minimum proximity of 100 m. Plots were located in the field by use of a hand-held GPS with an accuracy of ±5 m and searched by three independent observers.

CONTROL EFFECTIVENESS

Control effectiveness was estimated as the proportion of the population successfully treated as a function of the control effort applied to the grid cell. This control effort encompasses both searching for and treating any individuals found. The control effort function is assumed to be an asymptotic exponential function. When a small effort is applied, only the most obvious individuals are treated; as effort increases, we expect that an increasing proportion of time is spent searching for the smaller and less obvious individuals and so a larger proportion of the population will be treated.

Control effectiveness was estimated from data collected in 2007–2008. Willows were treated using a frill and fill technique (a small slit cut in each stem of a plant and the wound filled with herbicide) making it possible to identify treated willows subsequently. We classified 20 randomly located plants in each of five 1-ha plots as either treated or not treated and estimated control effort as the amount of time spent within each one-hectare grid (standardized to a team size of three) using GPS tracks recorded by the control team.

We modelled the number of plants treated as a binomial distribution:

$$X \sim B(p(c), n) \qquad \text{eqn 2}$$

where $p(c)$ is the probability of detecting and treating a willow given it is present and effort c was applied, while n is the number of willows that were monitored (20 in this case). The probability of detecting and controlling an individual, $p(c)$, is given by:

$$p(c) = 1 - e^{-\lambda c} \qquad \text{eqn 3}$$

where λ is a control effectiveness parameter. We fit the model using OpenBUGS 3·0·3 (http://www.openbugs.info/w/; Spiegelhalter *et al.* 2007) with uninformative priors. Parameter estimates are based on 100 000 samples after a 10 000 sample burn-in, which was more than sufficient for OpenBUGS to converge.

SPATIAL ALLOCATION MODEL

Hauser & McCarthy's (2009) spatial prioritization model was used to identify high-priority regions for one season's control (5 months). For each 20-m grid cell, the model uses the predicted likelihood of willow occurrence, the effectiveness of willow control and the benefits of willow control to prioritize locations. We assumed the relationship between control effort and the proportion of willows successfully treated is the same for all grid cells. For a given total budget of control effort, the optimization model then identifies the amount of control effort to be applied to each grid cell to minimize the expected total number of grid cells containing willow.

The model can account for spatial variation in the benefit attained by successful control. We consider two scenarios: first, we assume that a decrease in willow density in all areas is equally valued; in the second, decreasing willow density in mapped bogs or wet heaths is considered twice as beneficial as decreasing willow density in the rest of the landscape. We also consider two possible budgets for total control effort – 400 or 1000 person days per season (approximately \$250 000 or \$625 000). We assume 6 h of active control per day. Thus, we generated four allocation cases with unique benefit–budget combinations. The model was run in Matlab 7·8·0 (The MathWorks 2009). We present the results scaled to express the effort value allocated to each 20-m grid in units of hours per hectares, as we find this a more meaningful unit for managers.

Results

DISTRIBUTION MODEL

The Maxent model of control-adjusted occurrence predicts a widespread yet patchy distribution of environmentally suitable sites for *S. cinerea*. As expected, a reduction in the predicted likelihood of occurrence resulted in areas subject to intensive (and well documented) previous control effort (Fig. 1a,b); predictions with a high likelihood of occurrence ($>0{\cdot}75$ relative suitability) remained only in areas which received minimal or no control. Approximately 136 ha (0·01% of the study area) are still estimated to contain highly suitable habitat for *S. cinerea*, a reduction of 61% from the precontrol estimate.

The three variables with the most predictive power were topographic position, geological substrate and fire severity. This makes ecological sense as *S. cinerea* readily colonizes low-lying, high moisture sites that have experienced disturbance (i.e. burnt bog and wet heath communities). Aspect, slope and wetness index provided the lowest contribution to the model. Wetness index was a surprisingly poor predictor, which is probably because of correlation with topographic position (Spearman's $r = -0{\cdot}404$).

Validating the control-adjusted model using the independent data set revealed the model to have good discrimination power [AUC: 0·818 (95% CI, 0·735, 0·902)]. Visual comparison of predictions revealed a close alignment to the distribution of bogs, wet heaths and drainage lines. A concentration of suitable habitat is predicted to occur in the twice-burnt north-western region. However, as this area has also been the subject of considerable control effort, the likelihood of occupancy is approximately half the estimate for environmental suitability.

CONTROL EFFECTIVENESS

Data collected to estimate control effectiveness show that control staff tend to spend 3–4 h ha^{-1} controlling willows and are treating roughly 60% of individuals. Based on the data collected, we estimated λ as 0·0057 ($\pm$0·0007) ha min^{-1} (Fig. 2). The data were fit well by the negative exponential relationship (assuming a constant control rate, eqn 3) despite the small sample size.

SPATIAL ALLOCATION OF CONTROL EFFORT

The output of the spatial prioritization model is the amount of control effort (h ha^{-1}) allocated to each 20-m grid cell that minimizes the total expected probability of occurrence across the landscape. We show, as an example, the allocation of effort when we have the smaller budget of 400 person days (Fig. 1c). The amount of effort allocated to a given area varies between 0 and 2·8 h ha^{-1} with many areas not being treated. This amount of effort corresponds to an expected proportion of willows treated of 0–62% (Fig. 2). If reducing willows in mapped bogs is considered a priority, then the distribution of effort changes, with more effort concentrated in bogs (Fig. 1d). When bogs are prioritized, effort ranges from 0 to 4·2 h ha^{-1} with a predicted maximum proportion treated of 76% (Fig. 2).

The total area to be controlled depends on the budget available and how we value willow absence across space. When we value all areas equally and have a budget of 400 person days, control is allocated to 2702 ha (15% of the area). A budget of 1000 person days increases coverage to 4904 ha (27% of the area). If we value some areas more highly (e.g. bogs), the total area controlled tends to be reduced as effort is concentrated on the high-benefit areas. For example, with a budget of 400 person days when twice the benefit is gained from controlling willows in bogs, the area controlled reduces by 3% to 2166 ha. Similarly, when the budget is 1000 person days, the area controlled is 4343 ha or 24% of the area. Note that it is not just the total area but also the intensity of effort at selected sites that changes (Fig. 3a,b).

Prioritization of effort can be summarized by plotting the recommended time spent on survey and treatment (h ha^{-1}) as a function of the relative environmental suitability of the site

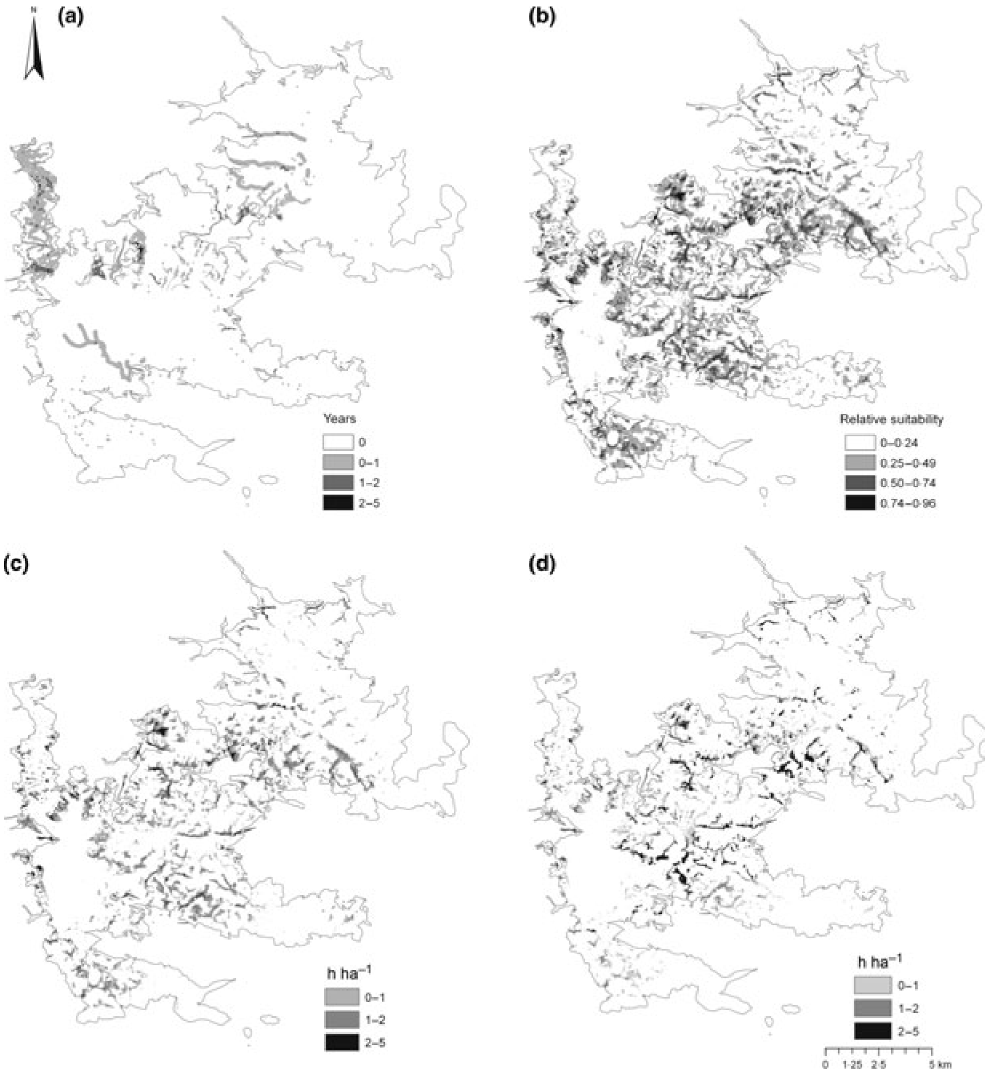

Fig. 1. Study area illustrating the (a) estimated intensity of *Salix cinerea* control during the years 2004–2008, (b) the potential distribution of *S. cinerea* accounting for control, (c) spatially prioritized control effort assuming a budget of 400 person days, with control weighted equally across all vegetation types and (d) the prioritization when double benefits are assigned to control in bog and wet heath vegetation.

(Fig. 3a,b). This relationship determines which sites warrant control, allocating longer periods as the suitability increases. In all scenarios, there exists a suitability threshold below which sites are not targeted for control. The threshold lowers (i.e. more sites are targeted for control) when a larger budget is available. The minimum likelihood of willow occurrence for which control effort is recommended depends on the budget, control effectiveness and whether bogs are prioritized. When the benefits associated with removing willow from all vegetation types are equal (Fig. 3a,b, solid lines), the recommended control time depends solely on the predicted likelihood of occurrence. In contrast, when removing willows from bog vegetation accrues double the benefit (i.e. bogs have higher conservation value), the recommended control times for bog sites are longer than for non-bog sites with equivalent environmental suitability (Fig. 3a,b, compare dot-dashed line to dotted line). This additional effort per site is substantially larger than the reduction in effort per non-bog site because bog sites make up only a small proportion of the landscape (Fig. 3c).

The model tends to recommend that less effort be expended in each area than was measured when monitoring the effectiveness of control activities. Greater than half a day's effort (>4 h) is recommended by the model only for those few sites where the likelihood of occupancy is very high (Fig. 3a,b) and either greater value is allocated to controlling willow in bogs (Fig. 3a) or budgets are high (Fig. 3b).

Discussion

In a resource-constrained context, it is important to prioritize management activities carefully. This means we must focus on activities that are efficient (Epanchin-Niell & Hastings 2010). Landscape-scale analyses can provide managers with a

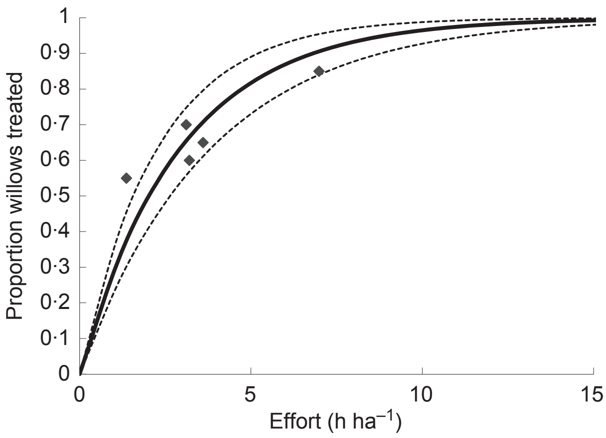

Fig. 2. Proportion of willows treated as a function of control effort. The solid line is the predicted proportion when a negative exponential relationship was fit to the data (eqn 3). Dashed lines are 95% credible intervals. Points indicate the data used to fit the model.

comprehensive overview of the potential scale of infestations and enable exploration of alternate management strategies. In this study, we identified high-priority locations for willow control that managers should aim to address over the course of a season. We have shown how integrating two analytical techniques, an optimization model and an empirical distribution model, can offer a better outcome for management by increasing the efficiency of invasive species control.

The resulting spatial allocation suggests visiting sites where the species is most likely to occur and exerting a moderate amount of effort at these sites. This strategy follows the well-accepted premise of directing effort to areas containing suitable habitat for pest establishment and persistence (Buchan & Padilla 2000; Underwood, Kinger & Moore 2004; Inglis *et al.* 2006; Fox *et al.* 2009). Our results go further and demonstrate that by aiming for quantity (by covering more ground) rather than quality, it will be possible to detect and treat a greater proportion of the population. Therefore, rather than attempt to control all individuals at each location before moving on, it is better to apply a moderate level of effort at a number of locations. It should be noted however that our model does not consider the costs associated with travel; if substantial, they may reduce the efficiency of this broad coverage approach.

The number of sites that can be managed in a day is dependent upon each site's prescribed visit length and the proximity of sites to one another. We would recommend control efforts are concentrated in contiguous areas for periods of at least a day, therefore minimizing the need to account for travel time. The area that can be covered also depends upon target species density, team size and landscape.

Our strategy accommodates spatially varying valuation of the landscape. When there are greater benefits attained from conserving particular landscape elements over others, the optimal visit length is influenced by the site-specific benefits of control. We should continue to invest most effort in sites with the highest likelihood of species occurrence but also target sites where control offers the greatest benefit for longer visits.

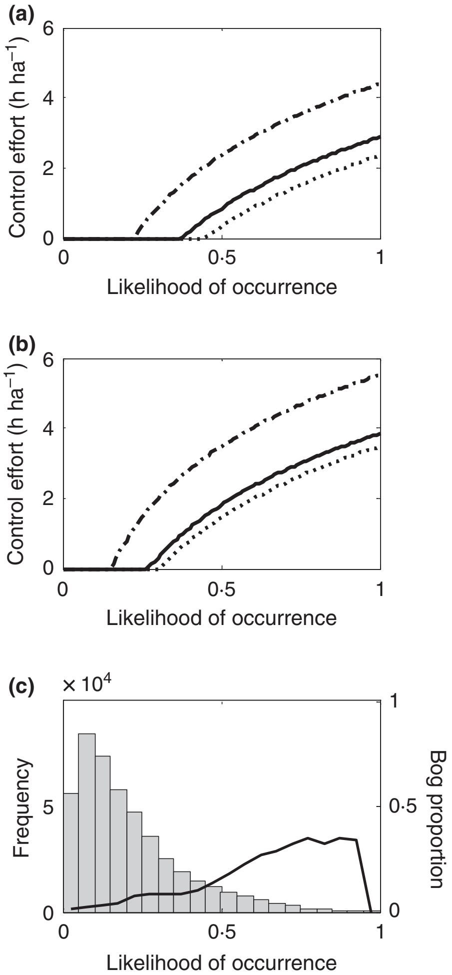

Fig. 3. Recommended control time (hours per hectare) as a function of the likelihood of occurrence at a site for *Salix cinerea* with a budget of (a) 400 person days and (b) 1000 person days. The control time also depends on whether benefits are weighted equally among all sites (solid line) or whether sites with bogs (dot-dashed line) accrue twice the benefits of sites without bogs (dotted line). (c) Frequency distribution of sites classified by likelihood of willow occurrence (shaded bars, left axis), and the proportion of such sites that have been classified as bogs (solid line, right axis).

The budget available for control operations also affects the number of sites included in the control plan and the time allocated to each site. A budget increase lowers the control allocation threshold (as determined by the relative likelihood of occurrence); therefore, sites where the species is less likely to occur will receive an allocation of control effort, and all sites can be allocated increased control time. Conversely, when there is a budget short-fall, the sites where control is highly effective will not have their allocation reduced as much as sites where control is less effective.

One of the advantages of this method is that the data requirements are modest and are typical of what managers already collect. The species distribution model was based on readily available presence data collected as a part of the control programme. New methods for building empirical species distribution models such as Maxent and boosted regression trees can fit good models using presence-only data (Elith *et al.* 2006). However, because the data were collected opportunistically, they are susceptible to bias reflecting previous control effort. Independent validation of the model showed that it provided good predictions for areas where work had not previously been carried out making us confident that the predictions are not overly biased in this case.

Accounting for past control effort is an important aspect of this analysis as it ensured predictions were relevant to the current on-ground situation. Past control records were of varying quality and were probably incomplete; hence, we used a simple approach to modelling past control effort as we had limited information about relative effort in different locations. This method of accounting for past control work also makes the model very simple to update to take future control effort into account.

The control effectiveness rate was estimated from GPS track data and post-treatment estimates of effectiveness. Collecting this data was quite challenging and meant we could only collect a limited number of replicates. In part, this was because we aimed to integrate search and treatment activities that occur over scales of hectares. Additionally, we attempted to estimate control effectiveness rates without the contractors' knowledge to minimize bias in the results. In retrospect, this bias was probably small compared with the uncertainty associated with the limited data collection. We would recommend a more focussed approach to estimating these parameters through the use of search trials (Garrard *et al.* 2008; Moore *et al.* 2011). Estimating control effectiveness is the most challenging aspect of the data requirements and may present the greatest barrier to implementing this framework. However, detection rates and control effectiveness estimates for similar species could initially be used to address novel situations.

The high uncertainty surrounding control effectiveness highlights the importance of sensitivity/or robustness analyses. In general, for budget-constrained control problems, a high value of λ allows managers to spread effort broadly with each site receiving less attention but sufficient control (Hauser & McCarthy 2009). When λ is low, control across the landscape is maximized by concentrating effort at fewer sites. Our estimation procedure for *S. cinerea* yielded control effectiveness estimate $\lambda = 0{\cdot}0057 \pm 0{\cdot}0007$, and the optimal allocation of control effort does not vary substantially across this range.

Ideally, occurrence and control effectiveness data will continue to be collected as management proceeds and can be used to update estimates for future resource allocation. In most circumstances, we expect that periodic updating and prioritization, e.g. once per season for *S. cinerea*, will be more feasible than continuous adaption. Furthermore, our control optimization operates on a single time-step. If the model was extended to minimize willow presence across multiple time-steps, then the strategy may change – for instance, it could be worthwhile to allocate more effort to fewer sites in any given time-step.

When developing a weed control strategy, it would be ideal to predict abundance, as opposed to likelihood of occurrence; however, sufficient data to model abundance through the landscape are rarely collected. This is unfortunate as it would enable the spatial allocation model to minimize expected abundance rather than presence. Nevertheless, the model developed has been useful for identifying areas of high suitability that had not been previously considered by the management agency.

The model also neglects dispersal or demographic processes. Other efforts to address invasive species management often include a dynamic dispersal or demographic component (Higgins, Richardson & Cowling 2000; Taylor & Hastings 2004; Buckley *et al.* 2005; Brown, Spector & Wu 2008). Although obtaining the data required for these steps is often expensive and time-consuming, the simulations form a crucial link in consideration of how rates and patterns of spread may impact upon the feasibility of eradication or containment efforts. The focus of this study is to control an existing population that established in response to fire. Until there is another fire, levels of establishment and spread on the Bogong High Plains are expected to be low. Hence, the problem we considered here is essentially a static one, and we did not attempt to include dispersal dynamics.

Conclusions and recommendations for management

Allocating control activities across a landscape that contains spatially disparate areas at risk, and where conservation agendas can preference actions to particular parts of the landscape, is a time-consuming and arduous task (Wadsworth *et al.* 2000). We have shown how a spatial model and a decision model can be combined to make this allocation. The output is measured as staff time and can be readily mapped to the landscape, allowing managers to visualize and interpret results.

The spatial allocation required a model that predicted invasive species occurrence across the landscape and another model of the relationship between control effort and control effectiveness. Obtaining these models can be resource intensive. While data to develop a species distribution model are often available, obtaining data to develop control effectiveness rates can be more difficult, and in some cases, expert judgment may be the only feasible option (Hauser & McCarthy 2009). Yet, as more studies of detection and control rates are completed, it is likely that estimates for similar species will become available.

The approach does not explicitly incorporate spread dynamics or identify optimal allocations through time, so it is a particularly useful approach for allocating effort in short-term cases or to situations where the system is relatively static, as it is in this case (*S. cinerea* germination on the Bogong High Plains is strongly dependent on rare fire events). However, the approach may have further utility when embedded into a broader decision framework. Long-term dynamic weed spread and management could be modelled by other means to identify how resources should be directed over space and time. Subsequently, our approach could be used for relatively static subsets of that management, such as allocating a control budget to a high-priority local area within a season. In either case, implementing invasive species management within a decision framework enables consistent data collection and allows the integration of budgetary constraints, ecology and management with the aim of maximizing management efficiency.

The framework highlights the importance of control effectiveness when allocating scarce resources to weed management. This requires that we audit the effectiveness of control through either field studies or experiments. Measures of how control effectiveness changes with effort (Fig. 3) enable a realistic assessment of how effective control methods can be. Furthermore, these rates can be used to identify the optimal allocation across space. Implementing these recommendations will require clearly stated strategies set by management for control staff (e.g. no action, control site for x hours, control until all removed), yet it may still be challenging for control staff to modify their effort. In particular, implementing a 'control for x hours only even if there is more to remove' strategy is likely to require an attitude shift from control staff. Control staff undertaking willow control have indicated that morale can drop if personnel feel that they are not finding or treating everything. Ensuring that control staff understand the larger picture would be crucial to the successful implementation of an intermediate-effort approach.

This allocation model provides an estimate of the area at high risk of invasion and tells us both where to start looking and also when to stop control efforts at one location and move on to another. By optimally distributing control effort when we have limited resources, the model reduces the subjectivity of decisions such as which populations to target immediately and which to control if time and money permit.

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