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SPECIAL ISSUE: HUMAN-MEDIATED INTRODUCTIONS OF AUSTRALIAN ACACIAS—A GLOBAL EXPERIMENT IN BIOGEOGRAPHY

Contain or eradicate? Optimizing the management goal for Australian acacia invasions in the face of uncertainty

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ABSTRACT

Aim To identify whether eradication or containment is expected to be the most cost-effective management goal for an isolated invasive population when knowledge about the current extent is uncertain.

Location Global and South Africa.

Methods We developed a decision analysis framework to analyse the best management goal for an invasive species population (eradication, containment or take no action) when knowledge about the current extent is uncertain. We used value of information analysis to identify when investment in learning about the extent will improve this decision-making and tested the sensitivity of the conclusions to different parameters (e.g. spread rate, maximum extent, and management efficacy and cost). The model was applied to *Acacia paradoxa* DC, an Australian shrub with an estimated invasive extent of 310 ha on Table Mountain, South Africa.

Results Under the parameters used, attempting eradication is cost-effective for infestations of up to 777 ha. However, if the invasion extent is poorly known, then attempting eradication is only cost-effective for infestations estimated as 296 ha or smaller. The value of learning is greatest (maximum of 8% saving) when infestation extent is poorly known and if it is close to the maximum extent for which attempting eradication is optimal. The optimal management action is most sensitive to the probability that the action succeeds (which depends on the extent), with the discount rate and cost of management also important, but spread rate less so. Over a 20-year time-horizon, attempting to eradicate *A. paradoxa* from South Africa is predicted to cost on average ZAR 8 million if the extent is known, and if our current estimate is poor, ZAR 33.6 million as opposed to ZAR 32.8 million for attempting containment.

Main conclusions Our framework evaluates the cost-effectiveness of attempting eradication or containment of an invasive population that takes uncertainty in population extent into account. We show that incorporating uncertainty in the analysis avoids overly optimistic beliefs about the effectiveness of management enabling better management decisions. For *A. paradoxa* in South Africa, attempting to eradicate is likely to be cost-effective, particularly if resources are allocated to better understand and improve management efficacy.

Keywords

***Acacia paradoxa*, biological invasions, decision theory, Early Detection and Rapid Response, environmental weeds, invasive alien species management, Table Mountain National Park, value of information.**

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INTRODUCTION

One of the few methods that results in long-term improvements of biodiversity indicators is the eradication of invasive alien species (McGeoch *et al.*, 2010), where eradication is defined as the elimination of every single individual of a species from an area to a point at which re-colonization is unlikely to occur (e.g. Myers *et al.*, 1998). However, an attempted eradication requires concerted sustained effort, and as such is likely to be successful only if there is a champion with the authority to ensure work progresses (Simberloff, 2009; Kraus & Duffy, 2010).

Assuming there is sufficient administrative support, a range of ecological and biological attributes have been identified, which will then affect the feasibility of eradication. Key attributes for plants include life-form (trees and shrubs are generally easier to eradicate than herbs), detectability prior to reproduction, capacity to form a long-lived soil seed bank, the potential for long-distance propagule dispersal and the availability of effective control methods (Myers *et al.*, 2000; Simberloff, 2003b; Panetta, 2009). One of the key criteria used as an indicator of whether an eradication attempt is likely to succeed is the spatial extent of the alien population, with eradication more likely when the area is small and when detection occurs soon after introduction, before seed banks or satellite populations are established. Indeed, resources required typically increase with the area infested, and the probability of success shows a concomitant decline (Myers *et al.*, 2000; Rejmanek & Pitcairn, 2002; Simberloff, 2003b; Woldendorp & Bomford, 2004; Panetta, 2007, 2009). The majority of successful plant eradications have been instigated soon after a population started spreading and dealt with a small spatial extent (e.g. < 100 ha; Mack & Lonsdale, 2002). Conversely, most attempts to eradicate invasive plant infestations in California larger than 1000 ha have failed (Rejmanek & Pitcairn, 2002). However, the spatial extent of a newly discovered alien species is usually poorly known, and methods to delimit the spatial extent efficiently are few (Panetta & Lawes, 2005; Leung *et al.*, 2010).

Even if eradication is technically feasible, it is still necessary to assess the economic viability of possible eradication; in particular, whether the costs of eradication can be justified in the context of the predicted benefits associated with the eradication (Panetta, 2009). While effective eradication depends on effective containment, if eradication is discarded as an option at an early stage, management resources can be redeployed to reduce impacts of the invasive alien or slow its spread (Myers *et al.*, 2000; Panetta, 2009). For example, resources could be allocated to limiting satellite populations rather than attempting to controlling established stands (Moody & Mack, 1988; Higgins *et al.*, 2000), or efforts could be focussed at the perimeter of existing populations to slow spread (e.g. by creating a barrier of unsuitable habitat). Similarly, there are benefits in introducing classical biological control agents as soon as practicably possible (Olckers, 2004), but, given the resources required, the inherent risks and the aim of reducing the target population to a low stable level, classical biological control should only be seriously considered if eradication is no longer the goal (McFadyen, 1998).

The decision to attempt eradication, therefore, is best made quickly, but it has to be made in the context of poorly known spatial extent (Panetta, 2009), poor population-level information and potentially rapidly expanding populations (Simberloff, 2003a).

Decision models are used increasingly in environmental management (Hauser *et al.*, 2006; Chadés *et al.*, 2008; Rout *et al.*, 2009a) and have previously been applied to invasive species control (Sharov & Liebhold, 1998; Higgins *et al.*, 2000; Shea & Possingham, 2000; Cacho *et al.*, 2006, 2008; Regan *et al.*, 2006; Bogich *et al.*, 2008; Rout *et al.*, 2009b; Epanchin-Niell & Hastings, 2010; Moore *et al.*, 2010; Shea *et al.*, 2010). Developing such models and facilitating their application in regional conservation planning and management is a key priority and challenge for conservation biogeography (Richardson & Whittaker, 2010). A decision model (1) allows us to evaluate how different strategies will contribute to meeting a specific objective or management goal, (2) provides a useful framework for trading off the cost and benefits of a number of different strategies and (3) is very useful for finding cost-effective management strategies. However, there is often uncertainty associated with a decision problem, including uncertainty in parameter estimates, which can make it difficult to identify an optimal strategy that is robust. As eradication attempts should be made soon after an invasive population is first detected, it is likely that uncertainty will be high (Mack & Lonsdale, 2002; Panetta, 2009). Explicitly recognizing this uncertainty and accounting for it in the analysis is critical to achieving a robust outcome. A particularly difficult issue is identifying when it is worthwhile investing in learning (i.e. research or monitoring that will reduce uncertainty), given that this choice will most likely take resources away from on-the-ground control efforts (Baxter & Possingham, 2011). We can either choose to invest solely in learning about the uncertain elements or integrate learning into the management process through active adaptive management, where management options are implemented in order to learn about the system (Walters, 1986; D'Evelyn *et al.*, 2008; McDonald-Madden *et al.*, 2010). How can we decide if it is worth investing in learning?

One approach is to use expected value of information analysis to identify whether uncertainty is important for our decision (Dakins, 1999; Yokota & Thompson, 2004; Claxton, 2008; Runge *et al.*, 2011). Expected value of information analysis is a well-established decision theory tool and is used extensively in medical decision-making and the design and evaluation of clinical trials (Felli & Hazen, 1998; Yokota & Thompson, 2004; Claxton, 2008) but is less commonly applied in an environmental context (Dakins, 1999; Ritchie *et al.*, 2004; Mantyniemi *et al.*, 2009), although it has recently been applied in conservation management (Polasky & Solow, 2001; Runge *et al.*, 2011). Expected value of information analysis measures how our expected performance would change if we were able to resolve or reduce our uncertainty prior to making our decision. The simplest measure to calculate is the expected value of perfect information (EVPI). EVPI measures the increase in expected performance if we were able to resolve all our uncertainty prior to making the management decision (Yokota & Thompson, 2004; Runge *et al.*, 2011). If EVPI is greater than zero, then finding out more about the system would improve our management decision (and so our management strategy). This means that our optimal strategy changes depending on the values of the parameters and our prior belief about the system. If expected performance is measured in monetary terms, EVPI can be interpreted as the maximum amount that we would pay to resolve our uncertainty (Yokota & Thompson, 2004).

The decision as to whether eradication or containment should be attempted needs to be made despite significant uncertainty about the extent of the infestation, the likely rate of spread, the effectiveness of management actions and the level of threat posed by the species. In this study, we develop a decision model to address when we should switch our management strategy from eradication to containment using a cost-benefit approach where our objective is to minimize the overall costs associated with invasion. Our decision model is very similar to that analysed by Cacho *et al.* (2008) to address the same question. However, we extend their analysis by using value of information analysis to examine how uncertainty in the extent of the infestation affects the decision and evaluates the potential for improving management outcomes through learning. We apply the decision model to assess the options of eradication and containment of the only known *Acacia paradoxa* population in South Africa, located in Table Mountain National Park (TMNP) in Cape Town (Zenni *et al.*, 2009).

Study system

As a group, Australian acacias include several globally important plant invaders (Richardson *et al.*, 2011). Moreover, the group, in general, poses a high risk of invading and causing significant impacts (Wilson *et al.*, 2011). However, while several eradication efforts are ongoing – for example *Acacia retinodes* is the target of an ongoing eradication programme on the island of Maui in Hawai'i (Kraus & Duffy, 2010) – none has yet been completed (Wilson *et al.*, 2011). This is despite several factors that make the group amenable to eradication: plants tend to be visible and distinctive, treating adult plants without creating further spread is reasonably easy, and the relatively large seeds means that controlling dispersal is much easier than for other plant invaders (such as many small-seeded grasses). The major limitation for controlling acacias is the long-lived seed banks (Gibson *et al.*, 2011), which means successful eradication will take sustained effort over decades (Wilson *et al.*, 2011).

Sixteen Australian acacias (and one in the closely related genus *Paraserianthes*) are currently regarded as invasive aliens in South Africa (van Wilgen *et al.*, 2011). While most are widespread invaders (Nel *et al.*, 2004), five have very restricted ranges and four (*A. adunca. A. implexa, A. paradoxa* and *A. stricta*) are classified under South African law as 'category 1a' invaders (i.e. require compulsory control, in essence legally mandated targets for eradication). *Acacia paradoxa* D.C. is a leguminous thorny shrub growing up to 4 m and is native to grassy woodlands and open forests in temperate and subtropical regions of south-eastern Australia. It produces hard seeds that form a dormant soil seed bank with germination stimulated by fire (Brown *et al.*, 2003). Seeds are thought to be dispersed by ants in the native range, and although the seed dispersal vectors in South Africa are not known, spread rates appear to be fairly slow (Zenni *et al.*, 2009). *Acacia paradoxa* has also been reported as a naturalized alien in Western Australia (Western Australian Herbarium, 2010), Tasmania (Simmons, 2009), New Zealand (Webb, 1980; Webb *et al.*, 1988), California (Fuller, 1967) and Israel (Dufor-Dror & Danin, 2004).

As part of a new national Early Detection and Rapid Response Programme funded by the Working for Water Programme, all Australian acacia species with limited alien ranges in South Africa are being assessed to determine whether they can be eradicated. Given that such eradication programmes focus solely on the target species and are set up separate from ongoing area-specific management, in South Africa (at least) eradication programmes represent an additional management cost.

METHODS

We develop a decision model to examine whether eradication of *A. paradoxa* in South Africa is economically cost-effective and to identify whether investing resources to more accurately determine the spatial extent of the existing population will assist in making this decision.

Decision model

The decision problem is 'What type of management action should be attempted for an infestation of current spatial extent x ha?' We consider three options—eradicate, contain, and take no action—and identify the values of x at which the optimal management action changes. We define the best management action as that which minimizes the total costs (i.e. the sum of management costs and production/amenity losses (Fig. 1; see Appendix S1 in Supporting Information for the full model description)). To do this, we must define the potential management actions and their associated costs.

First, the goal of eradication is to remove the entire population (every last individual including all seeds). This requires extirpating the existing population while simultaneously stopping spread (containment). The infested area (and an additional containment zone) will need to be searched and treated over an extended period for eradication to be achieved. Hence, we expect eradication costs to increase in proportion to the area infested. In this framework, we assume that it is a simple linear relationship that does not take into account project initiation costs that are disproportionate to area, nor any potential economies of scale for treating large areas.

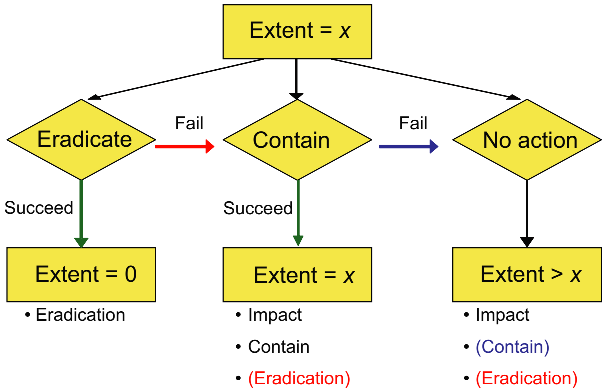

Figure 1 The conceptual model used to decide the best action to attempt for managing an infestation of x ha. There are three actions: attempt eradication, attempt containment and take no action. The diagram shows the possible outcomes resulting in action. The cost associated with each action is summarized below the outcome. Costs in brackets are not always incurred and depend on the path by which the outcome was achieved.

Second, in the event that eradication is unfeasible or an eradication effort fails, management can focus on containment. We assume that containment stops the spread of the invasion. Containment is achieved here by creating a containment zone around the perimeter of the infestation of width d, where d is the radial growth rate of the population, and searching and treating all individuals that establish in the containment zone. While treating the main infestation might also contribute to containment, for example by reducing seed production, in this model we consider the perimeter costs to dominate and so assume that containment costs are proportional to the area of the containment zone (given the spatial extent is roughly circular).

The third option that we consider is to take no action and let the invasion take its course. This 'strategy' provides a baseline with which we can compare the management strategies. If we take no action, we assume that the infestation grows as a circle with a radial growth rate (d) that decreases as the size of the infestation approaches the maximum extent (K), which specifies the maximum possible extent that the species could occupy. Note that the 'no action' option is included as a baseline and does not represent a general area management strategy.

We combine estimates of spread rate and maximum extent with estimated cost of the infestation to produce an estimate of the losses associated with the infestation through time. This impact loss includes all production, biodiversity and amenity losses that accrue as a result of the area that is infested. For example, impacts associated with Australian acacia invasions in South Africa include water loss, reduced productivity of grazing, loss of biodiversity, changes to the nitrogen cycle and reduced recreational amenity (de Wit *et al.*, 2001; Le Maitre *et al.*, 2011).

The total expected cost of the infestation for each action is the sum of the management cost (*Cost*) and the loss function (*Loss*) for that action (see Appendix S1 for specification of cost and loss functions). The optimal action for a given infestation size is that which has the smallest total expected cost at that infestation size. We find the critical values when the total expected costs of the different actions are equal.

$$\begin{aligned} x_c &: Cost(E) + Loss(E) = Cost(C) + Loss(C) \\ x_n &: Cost(C) + Loss(C) = Loss(N) \end{aligned} \tag{1}$$

These values indicate the extent of the infestation when the different actions become optimal: x_c is the extent when we should switch from eradication (E) to containment (C), and x_n is the extent when it is optimal to take no action (N).

Using a similar approach to Cacho *et al.* (2008), we focus our analysis on these two decision thresholds: (1) the extent of infestation when we change our action from *eradicate* to *contain* (when the expected combined losses and cost of eradication and containment are equal) and (2) the extent of infestation when we change our action from *contain* to *no action* (when the expected combined losses and cost of containment and taking no action are equal). It is not possible to derive an explicit solution for these equations, so we solved the equations numerically using the zeros function in the software package MATLAB R2009a (Mathworks Inc., Natick, Massachusetts, USA).

Incorporating uncertainty and the value of information

We have uncertainty in all the parameters and wish to understand how this will impact our decision. In this study, we focus on uncertainty in the extent of the infestation. Suppose that we have an estimate of the area of extent but we are uncertain about the value (we have some measure of standard deviation). Here, we assume that the true value is described by a triangular distribution (that need not be symmetrical) with mode x, minimum value $x_{\min}$ and maximum value $x_{\max}$.

The expected value of each action is found by integrating the combined losses and management costs over all possible extents, weighted by our prior belief in that extent (Appendix S1). Our optimal action is the action with the smallest expected value, and this provides us with our estimate of expected value under uncertainty, EV_u. We can also calculate our expected performance if we had full information and so knew the extent of the infestation prior to making our decision. We call this the expected value under certainty, EV_i. The EVPI is the improvement in performance gained by making decisions under certainty:

$$\mathrm{EVPI} = |\mathrm{EV}_i - \mathrm{EV}_u| \tag{2}$$

Sensitivity analysis

We examined how uncertainty in other parameters affected the model with a sensitivity analysis looking at the response of the model to perturbations from the current estimates. For each parameter in the model, we ran the model again for 10 levels of the parameter (keeping the others constant). The parameters range from 0.25 to 2.5 times the estimated value. We examined both changes in the total expected cost associated with the infestation (i.e. the cost-effectiveness of the decision) and changes in the decision thresholds (i.e. how much influence a parameter has on our decisions given our uncertainty in extent).

Parameterization for *Acacia paradoxa*

Parameter estimates (Table 1) were based on empirical data where available, and expert judgment where not. Further details are provided in Appendix S2. Parameters for the effectiveness of management, spread rate and the costs of impacts were the most difficult to estimate.

The current extent of the single *A. paradoxa* population (x) was estimated as 310 ha. Initial assessment of the infestation concluded that the infestation was approximately 295 ha in size (Zenni *et al.*, 2009), with a further 15 ha found on a follow-up survey (E. van Wyk, pers. comm.). We assume that it is much more likely that the estimated spatial extent is underestimated than overestimated and hence set $x_{\min}$ to 155 ha (half of the estimated value) and $x_{\max}$ to 1550 ha (5 times the estimated value). Spread rate was estimated assuming that the species was introduced 120 years ago (Zenni *et al.*, 2009) and that the spread rate has been constant since this time. The assumption of constant spread rate may underestimate current spread rates as documented invasions of other species through time suggest that there is often a lag between introduction and high rates of spread (Crooks, 2005). However, given that we have no information regarding changes in distribution through time, we did not consider it viable to attempt to estimate how spread rate might have changed.

We used two approaches to parameterize the maximum possible extent (K). First, we assumed that the population could spread throughout all suitable areas in southern Africa. To estimate the area of potential distribution for *A. paradoxa* in southern Africa, we used the bioclimatic niche model CLIMEX (Sutherst & Maywald, 1985; Sutherst *et al.*, 2007; see Appendix S2, Table S1) built on and projected with the CliMond V1 global climate data set at 10' resolution (Kritcos *et al.*, 2011). We assumed that the maximum extent equalled the CLIMEX-derived potential distribution. We consider this an upper bound for the maximum extent as it does not take into account other environmental factors or biotic interactions that might limit species distributions. We also considered the case if maximum extent was constrained to TMNP. This second approach evaluates the efficacy of the different management approaches within the context of the park alone. We used the full area of TMNP as the maximum extent; this is again an upper bound as it assumes the entire park is suitable. This latter scenario was motivated by the limited opportunities for dispersal from the park (TMNP is surrounded by the city of Cape Town and the Atlantic Ocean). The results obtained for both scenarios were qualitatively similar, and as such, we present the TMNP results in Appendix S3.

There is very little information about the effectiveness of eradication attempts or the effectiveness of containment for any invasive plant. In a rare evaluation of effectiveness, Rejmanek & Pitcairn (2002) analysed data from the California Department of Food and Agriculture describing 56 eradication attempts for 18 plant species over the period 1972–2000 and reported success as a function of infestation size. They found that eradication success was approximately 33% for species with a spatial extent between 0.1 and 100 ha and 25% for a

Table 1 Definition of the decision model parameters and the values of the parameters used for the example of *Acacia paradoxa* in South Africa.

Parameter	Definition	Units	Value
x	Estimated current extent of area that requires treatment	ha	310
$x_{\min}$	Minimum possible value of x	ha	155 (0.5x)
$x_{\max}$	Maximum possible value of x	ha	1550 (5x)
c_{e_ann}	Cost of eradication per ha per year	ZAR ha^{-1} year^{-1}	1335
e_t	Expected time to eradication	year	20
c_e	Total cost of eradication per ha assuming discount rate δ and a 20-year eradication programme	ZAR ha^{-1}	11,644
a_e	The extent at which the probability of failure of eradication is 50%	ha	750
m_e	How steep the failure curve for eradication is near the inflection point		0.005
c_{c_ann}	Annual cost of containment per ha of containment zone	ZAR ha^{-1} year^{-1}	454
c_c	Total cost of containment per ha of containment zone assuming discount rate of δ.	ZAR ha^{-1}	14,018
a_c	The extent at which the probability of failure of containment is 50%	ha	1500
m_c	How steep the failure curve for containment is near the inflection point		0.005
c_i	Cost of infestation	ZAR ha^{-1} year^{-1}	1701
d	Radial growth rate	100 m year^{-1}	1
K	Maximum extent that the species could occupy	ha	73,804,761
δ	The discount rate used to calculate the total expected cost of the infestation when left unchecked, the total expected cost of containment and the total expected cost of eradication	year^{-1}	0.05

spatial extent between 100 and 1000 ha. There were no reported eradications (and few attempts) for infestations > 1000 ha. However, the data set varied substantially in the amount of effort allocated and species-specific life histories and traits (e.g. it included many plant species that are small and difficult to detect). In a separate study of eradications, Panetta (2009) cited only one terrestrial eradication of gross area > 1000 ha (net area 2480 ha), two eradications of gross infestation size between 100 and 1000 ha and seven eradications with gross area < 100 ha (net area refers to the area treated, whereas gross area refers to the area searched (Rejmanek & Pitcairn, 2002)). This track record, combined with expert opinion and our assumption of a 20-year programme, led us to choose a sigmoid-shaped curve (see Fig. S1) for the probability of successful eradication with the area for which there is a 50% probability of success, a_e, set at 750 ha and the steepness parameter, m_e, set to 0.005. This parameterization resulted in a relationship where small infestations had a high probability of eradication success, but infestations > 1000 ha were likely to fail. There is even less information regarding the likely success of effective containment (assuming ongoing funding). Based on discussions with experts familiar with undertaking alien acacia management in South Africa, we assumed that the curve had the same basic sigmoid shape but was likely to be more successful for larger infestations, so we set a_c to 1500 ha (corresponding to a circumference of 13,729 m).

Treatment costs for high-density and medium-density populations were provided by the Working for Water Programme for the on-ground management of invasive Australian acacias in South Africa. We used their estimated cost of treating medium-density infestations (ZAR 1335 ha^{-1}) as our annual estimate of eradicating an infestation. We estimated that it would take 20 years to successfully eradicate the invasion assuming annual physical removal of individuals and that soil-stored seed would be depleted through high rates of post-fire germination (fires occur regularly at *c.* 5-year intervals within the National Park). The total cost of eradication was calculated assuming that annual treatments were undertaken each year at a fixed cost with discount rate, δ. We estimated the cost of containment per 100 m of perimeter using cost data on recent surveys for *A. paradoxa* assuming that the main activity associated with containment is to search the perimeter and physically remove any detected individuals. We then calculated the total cost of containment assuming that this cost was going to be incurred every year with discount rate, δ.

Estimates of the cost of impact were based on recent work undertaken to assess the environmental benefits associated with invasive species management programmes in South Africa. Locally applicable negative impacts of invasive acacia include reduction in surface stream flow, loss of biodiversity, changes to the frequency and intensity of fires, increase in erosion, destabilization of river banks, loss of recreational opportunities, reduced aesthetic appeal, nitrogen pollution and loss of grazing potential (de Wit *et al.*, 2001). All of these impacts have not been quantified specifically for *A. paradoxa*, so we used water use and grazing potential measures for *A. cyclops* and the biodiversity impacts associated with acacia invasions in South Africa generally. The overall cost of infestation was calculated as the sum of costs due to water use, lost grazing potential and biodiversity loss. All costs are reported in ZAR at 2010 values.

RESULTS

Eradicate or contain?

The model predicts that eradication is the optimal management strategy for *A. paradoxa* infestation sizes up to 777 ha with containment the optimal strategy for infestations between 777 and 2465 ha (Fig. 2a). For infestations larger than this, the model predicts that containment is unlikely to be successful and so the 'no action' approach is optimal by default.

Hence, the model predicts that the current optimal strategy for the existing population in TMNP (infestation size of 310 ha) is to attempt eradication. This choice has an expected cost over the 20-year assessment timeframe of ZAR 8 million, compared with an expected cost of ZAR 12 million if the containment strategy is attempted, or a cost of ZAR 146 million (through impacts on water loss, reduced grazing potential and loss of biodiversity) if no action is taken. The total expected cost of attempting eradication (ZAR 8 million) is greater than the cost of the eradication programme (which is

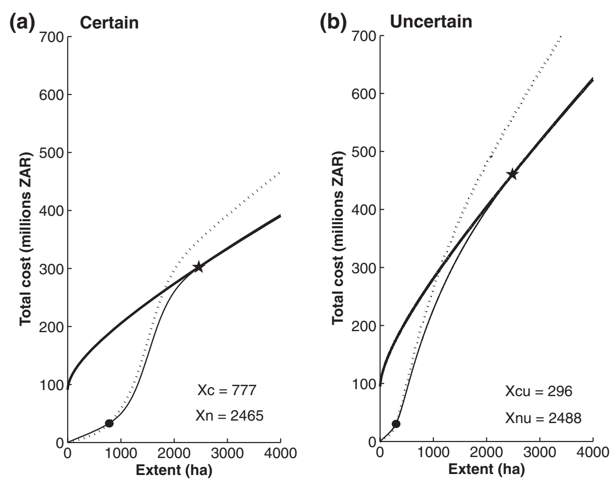

Figure 2 The expected total cost (losses caused plus management costs) as a function of the extent of the infestation when (a) there is no uncertainty in extent and (b) uncertainty in extent is taken into account. The dark solid line is the expected loss when no management is attempted. The dashed line is the expected loss for the eradication action, and the thin solid line is the expected loss when the containment strategy is used. The circle indicates the critical point to change from eradication to containment (x_c), and the star indicates the critical point to change from containment to doing nothing (x_n). Parameters are described in Table 1.

ZAR 5.4 million spread over 20 years). This difference reflects the additional costs incurred if management fails. For a spatial extent of 310 ha, eradication has a probability of failure of 10%, and containment a failure probability of 0.2%.

Including uncertainty and value of information analysis

If the uncertainty in extent is considered in the analysis, the eradication–containment threshold declines from 777 to 296 ha. The size of the infestation for which eradication is optimal is much smaller than if uncertainty is ignored, reflecting the high chance that we have underestimated the magnitude of the infestation. The feasibility of eradication of the *A. paradoxa* population is no longer optimal, and there is now a much smaller difference between the expected cost of eradication and containment. The expected cost of eradication is ZAR 33.6 million, while the expected cost of containment is ZAR 32.8 million (Fig. 2b). The expected cost associated with either management action is substantially higher when uncertainty is considered because potentially larger infestations are more expensive to treat, and management is more likely to fail.

Of course, this uncertainty can potentially be resolved. Using an analysis of the expected value of information, we calculate the value of resolving this uncertainty by comparing the expected cost of the best strategy under uncertainty (in this case containment) with the expected cost if we knew the exact extent prior to making our decision (i.e. we had perfect information). The difference is the EVPI, and, in this case, it is ZAR 2.6 million, which represents an 8% gain in performance. This value provides an upper bound on the amount that we could hope to save by making a better informed decision if we invested in learning about the extent.

We can also calculate how the value of information changes depending on the estimate of extent. We calculated the value of information if estimated extent, x, varied from 0 to 4000 ha assuming $x_{\min} = 0.5x$ and $x_{\max} = 5x$ and the parameter values used for *A. paradoxa* (Fig. 3a). The value of information peaks at the decision thresholds where the optimal strategy changes (296 and 2488 ha; Fig. 3a). For *A. paradoxa*, the current estimated infestation size (310 ha) is very close to the eradicate–contain threshold, and so the EVPI is close to the maximum, suggesting that learning would have a substantial pay-off in this case. When viewed as a percentage of total costs (Fig. 3b), proportional improvement is greatest at the eradication–containment decision threshold with a maximum saving of 8%.

Sensitivity analysis

We also investigated the sensitivity of the model by examining how parameters affected the expected performance of management measured as the total expected cost of the infestation (Fig. 4). Unsurprisingly, total costs are greatest if the discount rate is low (Fig. 4b). The total expected cost of the infestation

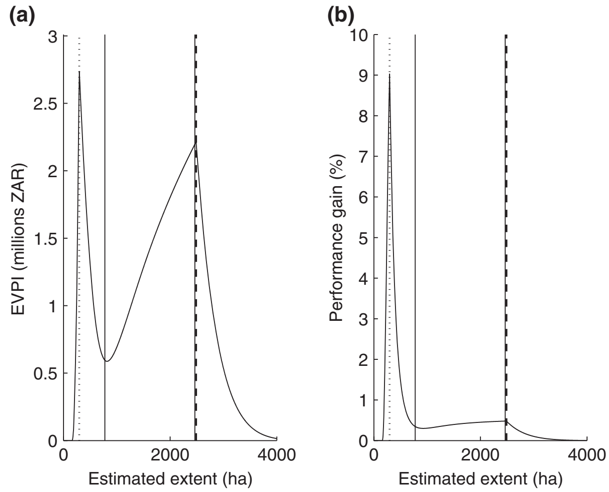

Figure 3 The effect of estimated extent on (a) expected value of perfect information and (b) the performance gain (%). The vertical solid lines indicate the decision thresholds ignoring uncertainty in extent. The vertical dotted line indicates the extent where the optimal action changes from eradicate to contain taking uncertainty into account, and the vertical dashed line indicates the extent where the optimal action changes from contain to no action when uncertainty is factored in.

(represented as a proportion of the baseline cost) increases substantially with the rate of spread (Fig. 4a) and the cost of the infestation (Fig. 4b), and decreases as the effectiveness of management increases relative to the initial extent (Fig. 4a). The total expected cost of the infestation increases only slightly as the cost of either management action increases (Fig. 4b). The maximum extent has very little effect on total expected cost.

We also examined how the value of the decision threshold changed with key parameters, which reflects the potential for these parameters to affect our decision space and hence is likely to have a greater impact on our decision (Fig. 5). The decision thresholds depend most strongly on the parameters that describe the effectiveness of the management actions, with the eradication–containment threshold increasing with the eradication effectiveness. The eradication–containment threshold increases as the cost of the infestation (and hence the threat of the infestation) increases, but declines as the cost of eradication increases and to a lesser extent as expected time to eradication and the discount rate increase (Fig. 5b). The decision to switch from eradication to containment is unaffected by the spread rate, the maximum extent, the effectiveness of containment (Fig. 5a) or the cost of containment (Fig. 5b).

The containment–no action threshold is most sensitive to the effectiveness of containment with the threshold increasing as effectiveness increases (Fig. 5a). The threshold also increases as the cost of the infestation (Fig. 5b) increases, reflecting the increased value of management when the potential damage of the infestation increases. The threshold decreases as the cost of containment increases, reflecting

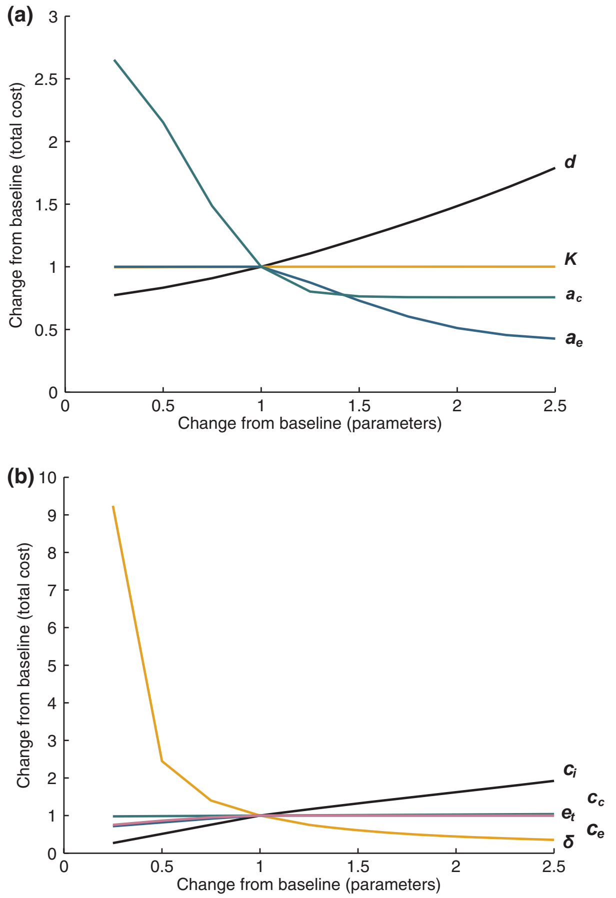

Figure 4 The results of the sensitivity analysis showing how the expected combined costs and losses change as each parameter varies. The *x* axis is the multiplier of the parameter estimates for *Acacia paradoxa* (Table 1). Each parameter was varied separately. The parameters considered were (a) spread rate (black), maximum extent (orange), 50% eradication extent (blue) and 50% containment extent (green) and (b) cost of infestation (black), discount rate (orange), cost of eradication (blue), cost of containment (green) and time to eradication (pink). Parameters are described in Table 1. Note that the scales on the *y*-axes differ.

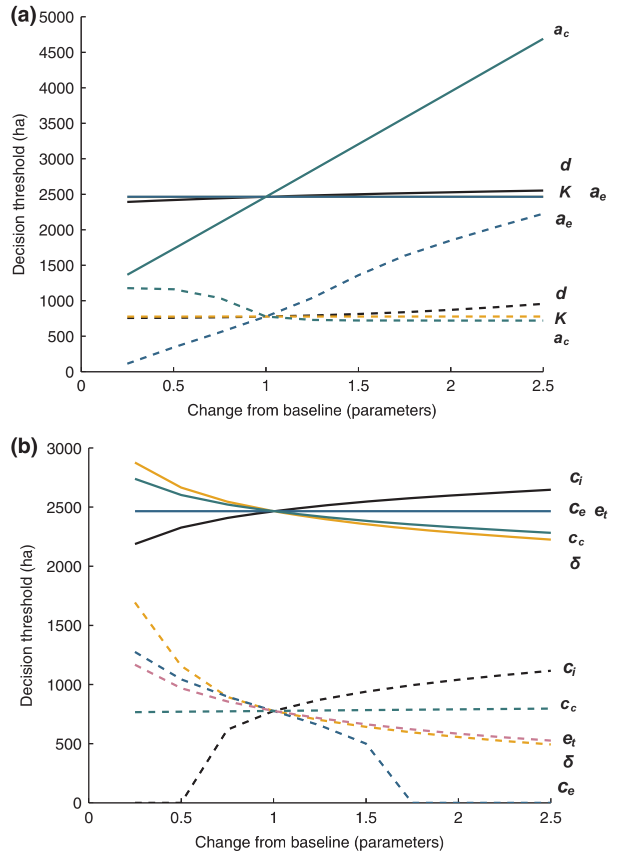

Figure 5 The results of the sensitivity analysis showing how the value of the decision thresholds x_c (dashed line) and x_n (solid line) changes as each parameter varies. The *x* axis is the multiplier of the parameter estimates for *Acacia paradoxa* (Table 1). Each parameter was varied separately. The parameters considered were (a) spread rate (black), maximum extent (orange), 50% eradication extent (blue) and 50% containment extent (green) and (b) cost of infestation (black), discount rate (orange), cost of eradication (blue), cost of containment (green) and time to eradication (pink). Parameters are described in Table 1. Note that the scales on the *y*-axes differ.

reduced efficiency of this management action. The threshold is insensitive to maximum extent, the cost, effectiveness or time to eradication.

DISCUSSION

Including uncertainty in extent

We have used decision theory and a cost-benefit framework to allocate management resources to minimize the combined costs and losses associated with the management of invasive species. For the case of *A. paradoxa* in South Africa, the model recommends that eradication is the optimal strategy if we do not consider uncertainty in extent. The maximum predicted extent that is economically feasible for eradication (777 ha) is consistent with previous work that used a similar decision model to assess the feasibility of eradication for woody weeds in Australia (Cacho *et al.*, 2008).

If we are confident about the accuracy of the estimated extent, then eradication is clearly the optimal strategy for *A. paradoxa* in South Africa, but our analysis shows that if we are uncertain about the estimated extent, the choice is much less clear. In our example, incorporating substantial uncertainty in the extent results in a much smaller extent for which eradication is the most cost-effective option (296 ha), suggesting that containment will be the most cost-effective action. However, for the current estimated extent (310 ha), the expected cost of containment and eradication is very similar with neither management action substantially better than the other. Explicitly incorporating uncertainty in extent also increased the expected cost of either management strategy by a factor of four. Hence, if we ignore uncertainty in the current extent in our analyses, we are likely to overestimate the effectiveness of management and substantially underestimate the cost.

What factors influence our decision?

The decision thresholds, which indicate the point at which the optimal strategy changes, are most sensitive to the effectiveness of the different management strategies and to a lesser degree the discount rate and the costs of management. These conclusions are similar to previous studies where allocation of effort depends on search efficiency (Hauser & McCarthy, 2009) and the relative effectiveness of quarantine and surveillance (Moore *et al.*, 2010). This highlights the importance of gaining a better understanding of management effectiveness both for identifying effective management strategies and for improving the probability of success. While conceptually simple, there have been few attempts to quantify the effectiveness of a suite management options or how management effectiveness and cost interact. Previous studies have shown that the effectiveness of invasive species management will improve with increasing allocation of resources (Rejmanek & Pitcairn, 2002; Woldendorp & Bomford, 2004). Managers undertaking eradication efforts tend to assume that they are applying enough effort to be effective; however, the effectiveness of the programme is rarely evaluated, and little attempt is made to find the allocation of effort that maximizes the probability of success. Efforts aimed at identifying the optimal level of effort to maximize the effectiveness of management would be valuable empirical and theoretical developments. The work presented here suggests that it will be difficult to make good management decisions in the absence of this information.

The spread rate has a substantial impact on the total cost of the invasion, but has a surprisingly small influence on the decision thresholds. This reflects that spread rate is included in the model as contributing to impact and the cost of management but does not influence the probability that management succeeds. This result appears to contrast with Cacho *et al.* (2008), who considered spread rate as one of the most important factors in determining the feasibility of an eradication attempt. However, in their model, spread rate contributed to the cost of management and implicitly the effectiveness of management as the possibility that a management action could fail was not incorporated in the model. The two studies can be reconciled if we note that it is the factors that determine the effectiveness and cost of management that determine the feasibility of eradication, and the contrast reflects differences in the way the two models are structured. Specifically, our model includes an explicit description of management effectiveness (probability of management failure) separate to management cost. The model presented here necessarily includes a very simple model of effectiveness that depends only on the size of the infestation as a crude proxy of the many biological and logistical factors likely to influence eradication including spread rate. Our analysis suggests that improving our understanding of the factors determining the effectiveness of eradication is critical to making good decisions and is an area of ongoing research.

The maximum extent had no influence on either the combined costs and losses or the decision thresholds. In our *A. paradoxa* example, the maximum extent has little impact because the invasion in South Africa would take hundreds to thousands of years to reach the maximum extent (depending on the spread rate), by which time discounting has rendered the contribution to the total cost negligible. This was true even for the scenario that focussed exclusively on impacts within the TMNP because in our example, spread rates are sufficiently slow that the extent of the problem is not restricted by maximum extent. In this model, it is the discount rate that effectively sets the maximum impact possible because it sets the timeframe over which incurred costs are considered. This is why the discount rate has such a large influence on the total cost of the invasion. It has much less effect on the decision threshold as these depend on the relatively likelihoods that the impacts are incurred (i.e. management fails), which depends more on the relative effectiveness of the management actions.

What is the value of learning?

The expected value of information analysis allows us to identify those circumstances when investment in learning is likely to result in more efficient management and shows that in this case, learning is most critical when the estimated extent is close to the eradication–containment decision threshold (taking uncertainty into account). The estimated size of the South African population of *A. paradoxa* is close to this threshold, and so the expected value of information is high in this case, suggesting that we could obtain the maximum value from learning about extent size. Even so, the value of information is modest (8%), indicating that there is somewhat limited value in undertaking such learning. This contrasts with a study aimed at managing fire ants in Australia that used an adaptive management analysis to highlight the importance of learning to maximize eradication probability (Baxter & Possingham, 2011).

The EVPI analysis presented here gives us an upper bound on the value that information would have on our ability to make a better decision because we assume that we can resolve all of the uncertainty when calculating EVPI. Value of information analysis is sensitive to the parameters and to the description of uncertainty (e.g. probability distribution used); hence, the robustness of the optimal strategy might change if we substantially alter our parameters or if we applied the model to other species with markedly different life history traits or management techniques. It is also worth noting that the model used here does not incorporate the potential for the invasion to become worse while the study proceeds (and hence increased costs of managing the invasion); EVPI probably overestimates the value of information in this model.

In addition, we have only considered the value of information regarding spatial extent. Uncertainty in other parameters may increase the EVPI (Dakins, 1999). Indeed, there is substantial uncertainty associated with many of the other parameters, and the sensitivity analysis suggests that uncertainty in some of these (notably the effectiveness of management) could be at least as significant as the uncertainty associated with the estimated size of the infestation. This additional uncertainty could be considered by extending the analysis to include uncertainty in all parameters and using partial value of information to assess the influence that individual parameter uncertainty has on the management decision (Claxton, 2008; Runge *et al.*, 2011). Including all sources of uncertainty in the parameters in the value of information analysis could provide a more robust analysis and be a useful next step (Dakins, 1999; Claxton, 2008).

Model assumptions and applicability to other systems

While we were motivated to develop this model to assess the case for eradication of *A. paradoxa* in South Africa, the model is sufficiently general that it could be usefully applied to any isolated population of plant or animal that spreads in a reasonably continuous way and for which eradication or containment is feasible. Although we have assumed that the invader spreads in all directions equally, in cases where there is reason to believe that spread would be substantially different from this (e.g. linear), the model could be adapted to accommodate this. Even so, a circular infestation will likely lead to conservative results with regard to eradication as containment is most efficient for circular shapes (circles have the largest area–circumference ratio). Species with high rates of long-distance dispersal or that have numerous disparate populations linked through dispersal may be better considered in a spatially explicit framework that enables one to evaluate not only the viability of eradication overall but also the order in which eradication of the individual populations is to be attempted.

The focus of this analysis was on evaluating the economic case for eradication, and so we have compared two possible management strategies (eradication and containment) against a baseline of taking no action. Other management strategies, such as the initiation of a biological control programme, or non-targeted control as part of broader management activities, could also be incorporated into this model framework.

The model developed here is focussed on a single decision point at an early point in the establishment and spread of an invading species when data are poor. Hence, we have not sought to solve the dynamic decision problem to identify how resources should be allocated each year (Cacho, 2006; Hauser *et al.*, 2006; Cacho *et al.*, 2007; Moore *et al.*, 2010). Of course, spatial and temporal variation will be important in determining how the eradication or containment strategies are implemented or when to declare eradication. Other decision tools have been developed to address these problems (Regan *et al.*, 2006; Hauser & McCarthy, 2009; Rout *et al.*, 2009b; Cacho *et al.*, 2010).

CONCLUSIONS

Our analysis suggests that eradication of the single *A. paradoxa* population in South Africa is currently a cost-effective strategy under realistic scenarios. The model also supports the general conclusion that as a strategy, eradication is likely to be economically desirable when management is considered in a long-term context, if impacts are high, or if an eradication attempt is likely to succeed. If we have substantial uncertainty about the current size of the infestation, the cost-effectiveness of eradication and containment is very similar for small infestation sizes. Investing effort in resolving the current infestation size has the potential to save a maximum of 8% of total expected cost (less the cost of gaining the information). Our analysis also suggests that management outcomes for *A. paradoxa* in South Africa would improve if substantial effort was invested in increasing the effectiveness and efficiency of eradication. Given the numerous other similar invasions of this species and others around the world, such an effort will be expected to have substantial additional benefits.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Figure S1 Eradication and containment failure curves.

Figure S2 Distribution records for *Acacia paradoxa* in Australia.

Figure S3 CLIMEX model projections for *Acacia paradoxa.*

Figure S4 Eradication and containment failure curves.

Table S1 Derived physiological parameters used in the CLIMEX models for *Acacia paradoxa*.

Appendix S1 Decision model.

Appendix S2 *Acacia paradoxa* parameters.

Appendix S3 Restricted maximum extent analysis.

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BIOSKETCH

Joslin Moore's research is focussed on using ecological theory as a tool to solve and inform applied ecological problems that will aid in the conservation and sustainable management of natural resources. She works closely with practitioners to address invasive species management problems using decision theory, population models and other quantitative tools.

Author contributions: J.L.M. and J.R.W. conceived the study; J.L.M. and M.C.R. formulated and analysed the model; J.L.M. and J.R.W. parameterized the model; B.L.W. collected the data and did the analysis for the CLIMEX model; and all authors contributed to the writing.

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