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IDEA AND PERSPECTIVE

Optimal eradication: when to stop looking for an invasive plant

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Abstract

The notion of being sure that you have completely eradicated an invasive species is fanciful because of imperfect detection and persistent seed banks. Eradication is commonly declared either on an *ad hoc* basis, on notions of seed bank longevity, or on setting arbitrary thresholds of 1% or 5% confidence that the species is not present. Rather than declaring eradication at some arbitrary level of confidence, we take an economic approach in which we stop looking when the expected costs outweigh the expected benefits. We develop theory that determines the number of years of absent surveys required to minimize the net expected cost. Given detection of a species is imperfect, the optimal stopping time is a trade-off between the cost of continued surveying and the cost of escape and damage if eradication is declared too soon. A simple rule of thumb compares well to the exact optimal solution using stochastic dynamic programming. Application of the approach to the eradication programme of *Helenium amarum* reveals that the actual stopping time was a precautionary one given the ranges for each parameter.

Keywords

decision theory, detectability, economic costs, eradication, invasive plants, stochastic dynamic programming, rule of thumb, weed.

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INTRODUCTION

Eradicating invasive plants requires the elimination of every potentially reproducing individual plant and seed from an area (Myers *et al.* 1998). Such endeavours require large amounts of funding, time and effort; so committing to such strategies requires confidence that eradication can be achieved (Panetta & Timmins 2004). However, it is almost impossible to verify total eradication of a species (Usher 1989; Reed 1996). Survey techniques are imprecise and seed banks are persistent resulting in imperfect detection rates. Instead eradication of invasive plants is commonly declared on an *ad hoc* basis, such as after 3 or 5 years without detection (Rejmanek & Pitcairn 2002) or after a period of no detection equal to the longevity of the seed bank (Woldendorp & Bomford 2004). Satisfying these requirements does not necessarily indicate that the invasive plant is no longer present or that survey efforts to find the species should cease.

Several quantitative methods for inferring eradication have been developed for animal pest management, and in conservation biology for inferring extinction. Barclay & Hargrove (2005) declared sites pest-free by assessing null trappings of insect pests to infer eradication. Solow (1993) and then several others (Burgman *et al.* (1995); McCarthy (1998) and Robert & Solow (2003) inferred extinction of rare or threatened species using sighting data and the time since the last sighting. Other studies look at the likelihood that a species is not present using measures of detectability (McArdle 1990; Parris *et al.* 1999; Kéry 2002), or how much effort is required to detect rare species or conversely infer extinction using ideas about statistical power (Green &

Young 1993; Reed 1996). While these methods may be adequate from a statistical point of view, directly utilizing the outcomes to inform management decisions can be problematic as the outcomes from hypothesis tests do not necessarily result in the most appropriate and cost-effective management strategy (Mapstone 1995; Field *et al.* 2004). Hypothesis tests typically use the conventional α-level or Type I error rate of 0.05 and, at best, aim at high statistical power to avoid a Type II error without any consideration of the consequences and economic costs of these errors. Being 95% or 99% sure that a species has been eradicated does not necessarily mean we should stop looking. While several authors warn that ignoring the potential costs and consequences of Type I and Type II errors will lead to ineffective management decisions and/or costly impacts (Nagel & Neef 1977; Mapstone 1995; Power *et al.* 1995) there are few examples of how to consider these costs (c.f. Field *et al.* 2004).

When an eradication programme for an invasive plant is nearing the end, fewer individuals may be sighted and several years may result in no sightings. Given confidence in complete eradication is virtually impossible, there are two possible choices when a species is not sighted for some time: (1) stop surveying and declare eradication with the risk that the species is still present and could escape (Type I error, α); or (2) continue to survey with the risk that the species is already eradicated and scarce economic resources are wasted (Type II error) (Reed 1996). Each of these decisions incurs a cost, and the best management decision is a trade-off between these costs, which we explore in this paper. We formulate the problem within a decision theoretic framework and explicitly consider the consequences and costs of each management decision (Shea & Possingham 2000; Possingham *et al.* 2001; Maguire 2004). We pose the question: how many years should we survey and not detect the species before stopping, to minimize expected costs? We propose a theory for the optimal time to stop looking for an invasive plant and declare eradication. Rather than declaring eradication at some arbitrary level of confidence, we take an economic approach. Surveys should cease when the expected costs of looking outweigh the expected benefits. We do this in two ways, firstly employing a simple rule of thumb and then by using stochastic dynamic programming (SDP) (Mangel & Clark 1988). SDP has the advantage of providing the exact optimal solution. The rule of thumb is approximate but it may be preferable as it is simple and easily applicable. We develop these models for questions relating to declaring eradication of invasive plants and apply them to the eradication programme for the invasive weed *Helenium amarum* in Queensland, Australia (Tomley & Panetta 2002).

METHODS AND MATERIALS

Rule of thumb

Consider a situation where an invasive plant is being removed from an isolated area where recolonization is unlikely. This is likely to be true when the infestation is the only one in the country or continent. For several years, annual surveys reveal no individuals. The question is: is it worth going back the next year to survey again or should we stop looking (and declare eradication)? If the objective is to minimize the net expected costs, NEC, then the formulation of the problem requires four main parameters: (1) the cost of annual surveys, C_s; (2) the expected cost of escape and damage, C_e, which includes the likelihood of escape; (3) the probability of detecting the species given it is present, q; and (4) the annual probability the species remains present, p. For instance, the NEC of stopping after each survey where the species is not detected is equal to the cost of surveying added to the expected cost of escape and damage given the species is present but went undetected in that year. For example, the NEC after one absent survey can be expressed as

$$NEC_1 = 0 + C_e \times p(1 - q). \quad (1)$$

No cost for surveying is incurred for the first absent survey as the decision process is only triggered after the first absent survey is completed. After two consecutive surveys that fail to detect the species, the NEC is the cost of the survey added to the cost of escape given that the species was present but went undetected in both the current year and the previous year. The NEC is represented as

$$NEC_2 = C_s + C_e \times [p(1 - q)]^2. \quad (2)$$

NEC can be generalized to any number of absent surveys, n, resulting in

$$NEC_n = (n - 1) \times C_s + C_e \times [p(1 - q)]^n. \quad (3)$$

The optimal number of consecutive zero surveys, n^*, that minimizes NEC can be calculated by minimizing eqn 3 and solving for n, to give

$$n^* = \frac{\ln\left\{\frac{-C_s}{C_e \times \ln(r)}\right\}}{\ln(r)}, \quad (4)$$

where $r = p(1-q)$ is the probability the invasive plant is not detected but is still present as either adults or seed.

We incorporate costs in two ways, (1) a constant cost over time, and (2) using a standard discount rate of $d = 0.05$ for costs incurred in the future (Sumaila & Walters 2005).

The discounted cost of surveys, $C_{\text{s-dis}}$, over n years is calculated according to eqn 5.

$$C_{\text{s-dis}} = C_{\text{s}}\left\{\frac{1-[1/(1+d)^n]}{d}\right\}. \tag{5}$$

For a one-off cost of escape and damage, the discounted cost, $C_{\text{e-dis1}}$, is calculated according to eqn 6.

$$C_{\text{e-dis1}} = \frac{C_{\text{e}}}{(1+d)^n}. \tag{6}$$

Stochastic dynamic programming

The above formulation of the costs ignores the possibility that the invasive plant will be seen in a future survey and further costs of survey and possible escape will be encountered. These possibilities can be accommodated by formulating a state-dependent decision process and solving the problem using SDP, a backward iterative procedure that finds the optimal state-dependent solution for a stochastic system (Mangel & Clark 1988). Utilizing SDP first requires development of a model of the state dynamics of the system (McCarthy *et al.* 2001). There are three states of the system; the invasive plant is (1) present on the site but goes undetected because adults are missed or the species is only present in the undetectable seed bank, (2) present and detected, or (3) absent. The observed state is the number of years for which the species is not seen (it can be absent or present but not detected).

The model for the dynamics of the system is the following. As in the rule of thumb, let p equal the annual probability of persistence and q, the probability of detecting the species if it is present. Let w_n be the probability of the site being occupied given the invasive plant was not seen during the last n surveys. w_n is updated using Bayes' theorem every year, depending on the outcome of the survey. If the invasive plant is observed, then the probability of presence is obviously equal to one and the variable n becomes zero. Thus, $w_0 = 1$.

If the species is not observed, then the value of n is incremented by one, and we use Bayes' theorem to update the probability of the species being present. Immediately prior to a survey, the probability that the species is present is equal to the probability it was present last year and persists for a year, so the prior probability of the species being present is w_np and the prior probability of it being absent is $1 - w_np$, given that it has not been seen in the n surveys prior to the current one. The posterior probability depends on the prior probability of presence and the probability of not seeing it under the two possible hypotheses, which are the species is present or absent. The probability of not observing the species when it is present equals $(1 - q)$, and 1 given the species is absent. Therefore, if the invasive plant is not seen in a survey, Bayes' theorem provides the updated (posterior) probability of the species being present

$$w_{n+1} = \frac{w_np(1-q)}{w_np(1-q)+1-pw_n}, \quad n > 0, \tag{7}$$

which simplifies to

$$w_{n+1} = \frac{w_np(1-q)}{1-w_npq}. \tag{8}$$

The optimal decision for year t can be found if it is assumed that all subsequent decisions (in years $t + 1$, $t + 2$, …, T) will be optimal. By setting conditions at the end of the management time horizon T we can obtain optimal decisions for all prior years. The SDP solution depends on defining probabilities of transition from one state to another and the value of being in different states.

The states in this problem are defined by the number of surveys that have elapsed since the last observation of the invasive plant, n. Therefore, if we saw the species in the previous year and are about to make a decision about whether to survey or not, $n = 0$. If the species was not seen last year, but was seen in the previous year, then $n = 1$, and so forth.

From one year to the next, changes in n depend on the outcome of the survey. The value of n can change to zero (if the species is seen) or to $n + 1$ (the species is not seen). The probability of transition $n \rightarrow 0$ is equal to the probability that the species was present in the previous year (w_n), survived (p) and was detected (q), so $\Pr(n \rightarrow 0) = w_npq$. The probability that n is incremented by one equals the probability of the species not being seen, so $\Pr(n \rightarrow n + 1) = 1 - \Pr(n \rightarrow 0) = 1 - w_npq$.

Knowing these transition probabilities allows us to calculate the expected costs of our decisions to stop or continue surveying this year. The expected cost of stopping $E_{\text{stop}}(n, t)$ is equal to the probability that the invasive plant was present in the previous year (w_n) multiplied by both the probability that it persists until this year (p) and the cost of escape (C_e). Thus,

$$E_{\text{stop}}(n,t) = w_npC_e. \tag{9}$$

The expected cost of surveying $E_{\text{survey}}(n, t)$ is the cost of an additional survey (C_s) plus the expected costs arising from the two possible outcomes for n (0 and $n + 1$) assuming that optimal management is undertaken in all years up to time T. Thus,

$$E_{\text{survey}}(n,t) = C_s + w_n pq E_{\text{opt}}(0,t+1) + (1 - w_n pq) E_{\text{opt}}(n+1,t+1) \quad (t < T), \\ = C_s \quad (t = T), \tag{10}$$

where E_{opt} represents the expected costs arising from future optimal decisions. For our purposes, E_{opt} is the lower expected cost of the two management options:

$$E_{\text{opt}}(n,t) = \min[E_{\text{stop}}(n,t), E_{\text{survey}}(n,t)]. \tag{11}$$

This tells us the optimal decision in each year t based on the number of previous negative surveys n, i.e. we continue to survey if $E_{\text{stop}}(n, t) > E_{\text{survey}}(n, t)$. Thus, the optimal stopping time n^* is the smallest value of n such that $E_{\text{stop}}(n, t) < E_{\text{survey}}(n, t)$, i.e. the smallest value of n such that the least expensive option is to stop surveying.

Example: *Helenium amarum*

To illustrate the method, we apply the rule of thumb to a case study of the eradication programme of *H. amarum* in Queensland, Australia. Commonly known as bitterweed, *H. amarum* is an annual herb from Mexico and the USA (Baskin & Baskin 1973). It was first detected in Queensland in 1953. It was presumably introduced by airfreight as the infestation was near an airfield used by the US military and spread to an area of over 50 ha (Tomley & Panetta 2002). *Helenium amarum* is toxic to stock causing weakness, diarrhoea, vomiting, and bitter undrinkable milk if ingested by milk producing animals. An eradication programme commenced in 1953, involving the application of herbicide via boom-spray, spraying individual plants and manual removal. The population declined and within 3 years only small patches of isolated plants could be found. Several surveys between 1959 and 1987 did not detect the species although it was found in subsequent years. Between 1988 and 1992 no plants were found and *H. amarum* was assumed to be eradicated after 5 years without detection (Tomley & Panetta 2002).

We parameterized the model with a range of plausible values based on available data (Table 1) to determine whether 5 years without detection was the optimal stopping time. Detection rates were estimated using time series of presence/absence data for *H. amarum* between 1953 and 1992. The probability of persistence, p, was calculated by utilizing information regarding the longevity of the seed bank (Tomley & Panetta 2002). While the estimates of these two parameters are approximate due to limited data on the species, more sophisticated estimation methods could be adopted with more information (see Mackenzie *et al.* 2002; Tyre *et al.* 2003; Wintle *et al.* 2004).

Table 1 The range of parameter values used in the *H. amarum* model

Model parameters	Range of values
Probability of detection, q	0.59–0.95 (0.83)
Probability of persistence, p	0.50–0.90 (0.8)
Probability of escape, P_{escape}	0.4–1.0 (0.5)
Probability of damage, P_{damage}	0.6–1.0 (0.7)
Cost ratio, $C_s : C_e$	1:197–1:1317 (1:354)

The values in parentheses were used as the best estimate parameter set.

Costs are represented as a ratio between the cost of surveying and the cost of escape and damage. The costs associated with a survey, C_s, can be calculated using the annual number of person hours needed to survey the infested area and any associated buffer areas, the wage per hour, and any additional operational costs. The cost of escape and damage is the expected cost if the invasive plant was to escape and cause more damage. We represent this cost (C_e) as the product of the probabilities of escape and damage, and the expected costs if these events eventuate, C_{damage} (eqn 12).

$$C_e = P_{\text{escape}} \times P_{\text{damage}} \times C_{\text{damage}}. \tag{12}$$

The cost of escape is the cost associated with a particular level of damage and this is likely to be different depending on the damage at different scales. For the purposes of illustration, we use the expected cost of damage to the dairy industry in South East Queensland if *H. amarum* was to escape. During 1972–1973, the total production value of the dairy industry (butter, cheese and milk) was estimated as *c.* \$54 710 000 year^{-1} (Sayer 1974). A widespread incursion of *H. amarum* is likely to have caused a loss of between [0.25%, 0.5%, 1.0%] of the total production value, including the production loss and the costs of further *H. amarum* control. This is equivalent to a cost ratio of 1 : 1013, with lower and upper bounds of [1 : 813, 1 : 1317], scaling for the year in which the decision was made, (i.e. 1992) and the ongoing annual costs to the industry, using a discount rate of 5%.

RESULTS

Using the rule of thumb, the net expected cost, NEC, as a function of the number of consecutive absent surveys declines to a point and then increases (Fig. 1). The minimum point on each curve (highlighted by the black dots) is the optimal survey time that minimizes the net expected cost. As the probability of the species being present and undetected, $r = p(1 - q)$, increases, the optimal

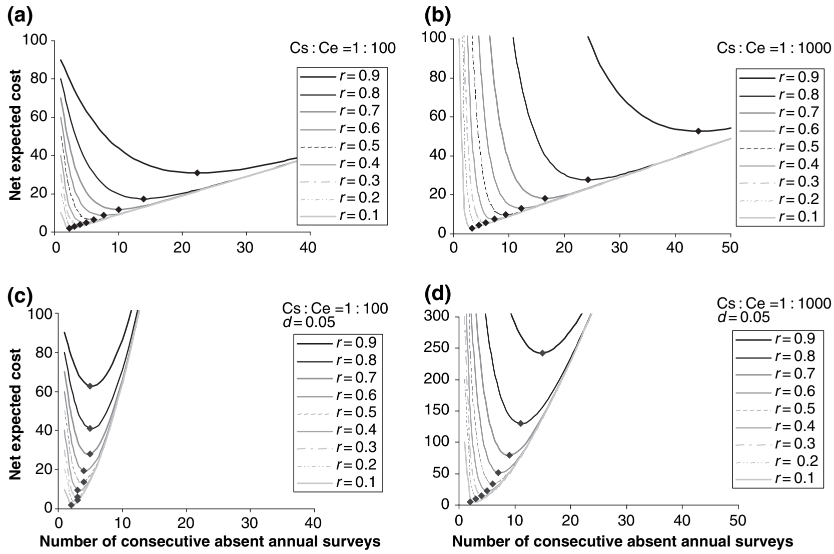

Figure 1 The rule of thumb. The net expected cost (NEC) as a function of the number of consecutive absent annual surveys for two different cost ratios, 1 : 100 and 1 : 1000, with and without a discount rate of 5%. The dots represent the optimal number of years before stopping that minimizes NEC.

stopping time ranges between 2 and 22 years for a cost ratio of 1 : 100 (Fig. 1a) and 3–44 years for a cost ratio of 1 : 1000 (Fig. 1b). The increases in r have a nonlinear effect on the optimal solution. When the cost ratio increases (i.e. from 1 : 100 to 1 : 1000) this nonlinearity becomes more obvious.

Including a discount rate of 5% reduced the optimal survey time for both cost ratios, particularly for large values of r. The optimal time to stop looking when costs are discounted ranges between 2 and 5 years for a cost ratio of 1 : 100 (Fig. 1c) and 2–15 years for a cost ratio of 1 : 1000 (Fig. 1d). This suggests that it is better to accept the potential costs of escape and damage in the future rather than invest in long-term surveys now. Other properties of the curves in Fig. 1 suggest that as the number of consecutive zero surveys increases, NEC converges for all values of r. The curves all eventually converge to NEC $\propto n \times C_s$ but only converge at values greater than the optimal solution.

The rule of thumb ignores the possibility that the species will be found prior to completing n^* surveys, so that further surveys would then be required. The SDP model incorporates this possibility and provides the exact solution to the problem. For a cost ratio of 1 : 100 the optimal solution for the rule of thumb closely maps on the SDP solution for varying levels of persistence and detection rates (Fig. 2). When persistence is high (> 0.8), the rule of thumb underestimates the optimal number of surveys by one or two surveys if the probability of detection is high ($q = 0.95$), and about five surveys if the probability of detection is very low ($q = 0.05$).

An interesting aspect emerges from Fig. 3. For the rule of thumb, for all relative costs, as $r = p(1 - q)$ increases, the optimal solution gradually increases to a point after which

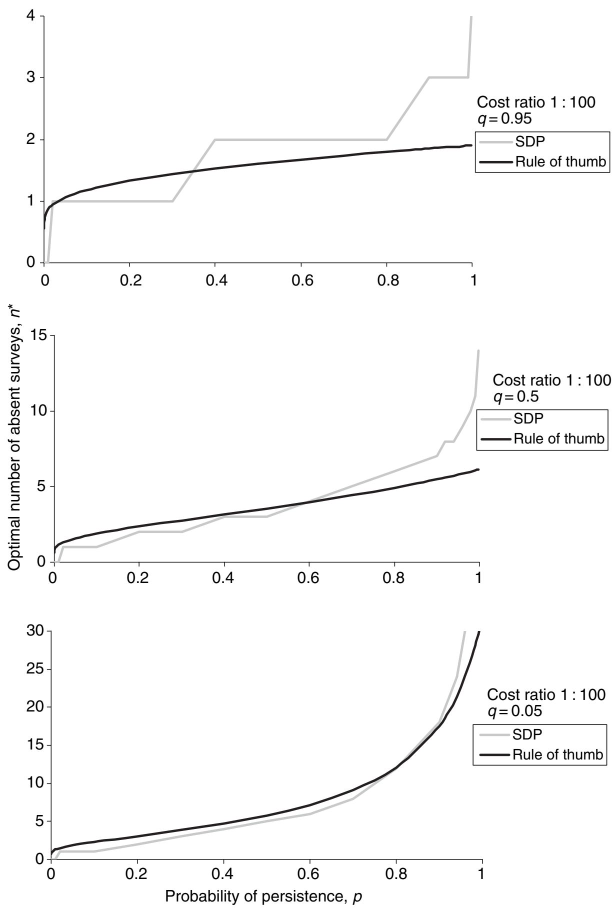

Figure 2 Comparison of the rule of thumb and SDP model. The optimal number of absent surveys as a function of the probability of persistence, p, for a cost ratio of 1 : 100 and three levels of detectability.

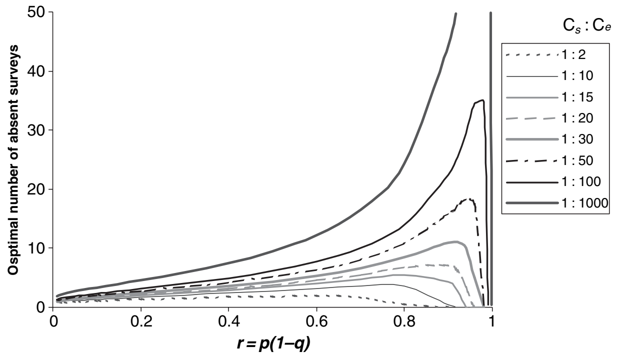

Figure 3 Rule of thumb, the optimal number of absent surveys as a function of the probability of the invasive species being present but going undetected, $r = p(1-q)$, for a number of cost ratios.

the optimal number of surveys decreases to zero. Hence, for all cost ratios, there is a point at which the optimal solution is to discontinue surveying if r is too large. In this circumstance, the cost of continued surveying is greater than the cost of escape and damage, and the best management decision is to not survey. For a cost ratio of 1 : 2, the optimal solution is not to continue surveying if r is > 0.7. Alternatively, for costs ratios larger than this, such as 1 : 1000, the point at which the optimal solution declines to zero is at a value of $r = 0.999$. With this same cost ratio, if r is reduced to 0.99 then the optimal solution is 230 consecutive zero surveys before we should stop surveying. These results were also evident using the SDP although only for very high values of p and $1 - q$.

Application of the model to the case study of *H. amarum* reveals that the actual time horizon of 5 years of no detection before declaring eradication was a precautionary decision for the range of values used (Fig. 4). The optimal time to stop looking for *H. amarum* given the parameter

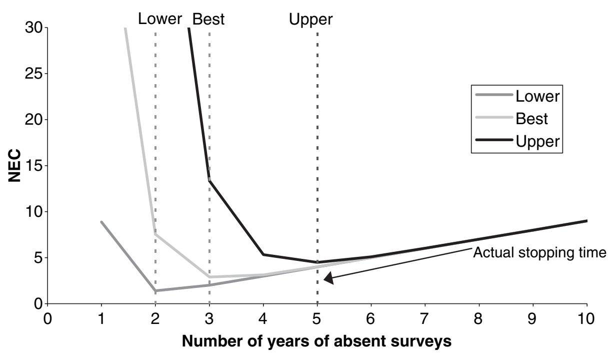

Figure 4 The net expected cost as a function of the number of years of absent surveys for lower, 'best' and upper parameter range combinations for *Helenium amarum* using the rule of thumb. Vertical lines represent the optimal solution for each parameter combination with the actual stopping time indicated.

estimates was at least 2 years and no more than 5 years with a best estimate of 3 years. Detection rates for *H. amarum* were high (> 0.8), resulting in fairly low optimal survey times.

DISCUSSION

Judgements about eradication are based on *ad hoc* notions of seed bank longevity or at best on null hypothesis significance tests that do not consider the costs and consequences of Type I and Type II error rates. Couching the problem within a decision theoretic framework provides an avenue for systematically investigating the tradeoffs within a management context that is transparent, repeatable and with the underlying assumptions laid bare.

We presented two algorithms for answering the question of when to stop looking for an invasive plant; a rule of thumb, and a stochastic process model solved using SDP. The results suggest that the rule of thumb is a good approximation of the SDP solution. The rule of thumb is a simplification of the SDP ignoring the possibility that further surveys may be required if the species is found prior to completing n^* surveys. However, this simplification only influences the outcomes when the probability of persistence is high and the probability of detection is very low ($q = 0.05$). In these cases, the solution from the rule of thumb underestimates the exact solution by about five surveys. In these situations, it is preferable to use the exact SDP solution for supporting decisions to stop looking or alternatively adopt monitoring regimes that are more likely to identify the persistent species.

Managers confronted with decisions regarding when to conclude eradication programmes are often not equipped with the resources necessary for undertaking mathematical algorithms such as SDP. The rule of thumb provides an accessible decision support tool that can be easily implemented by decision-makers to explore different scenarios and situations, provided they are aware of the model's limitations. In particular, the rule of thumb allows decision makers to examine how robust their decisions are to changes in parameter values and enables a systematic evaluation of the factors concerning eradication.

The results of the rule of thumb illustrate several aspects that were not initially obvious. As false-negative rates and persistence probabilities increase, small differences result in larger shifts in the optimal solution, indicating that uncertainty in these parameters has a multiplicative rather than additive effect on the optimal solution. This result highlights the importance of more precise estimates if false negative and persistence rates are at the higher end of the probability scale. If estimates for these parameters are at the lower end of the probability scale then precise estimates may be less important. Furthermore, when costs are discounted then the optimal stopping time is reduced, reflecting that costs in the present have a larger value than costs in the future and additional surveying may not be beneficial. Costs could also escalate at different rates – survey costs in the future will probably increase in line with national inflation rates but escape cost could also be dependent on agricultural changes in the region. Consequently, different discount rates could be appropriate.

As false negative rates and persistence probabilities increase, optimal stopping times increase to a point and then decrease to zero. This was evident for all cost ratios that we considered. This may have important implications for management as it suggests for some plant species that the best management strategy is to discontinue surveys and accept the potential costs of escape and damage because the required number of zero surveys before stopping would be more expensive. This is particularly true when the expected cost of escape is small compared with the annual cost of survey, the plant is more likely to have a long-lived seedbank (p high), or our detection success is poor (q high).

The philosophy taken in this paper is similar to the concept of triage (Possingham 2001), which encourages investment in management of those species that benefit the most. Under triage, there comes a point at which resources that are invested in an endangered species would be more efficiently spent elsewhere, even when there might be a substantial risk of extinction. In the current example, there comes a point where investment in further monitoring is not warranted if the cost of escape is sufficiently small. In these cases, it may be wiser to invest funding to offset the eventual cost of escape rather than surveying. Alternatively, changes in survey design that promote an increase in the detection rate may ultimately be less costly while more likely to avoid the eventual escape.

Applying the rule of thumb to the eradication programme of *H. amarum* illustrates that the decision to stop looking and declare eradication after 5 years was a precautionary one given the ranges for each parameter. The optimal range of years was 2–5 years. Coincidentally, this is the range of years where managers generally declare eradication. However, the detectability of *H. amarum* was generally high, in the order of 0.83, and is not necessarily indicative of all invasive species.

The approach used in this paper requires that the cost of escape is quantified. For *H. amarum*, we estimated the cost of escape based on economic losses to the dairy industry and on-going control costs. The cost of escape is more difficult to estimate when applying the rule of thumb to an invasive plant in a natural system, as the loss to an ecological system is not easily represented as an economic cost. In these situations, other utility functions may be more appropriate. Furthermore, the cost of escape also depends on the scale at which the potential damage is envisaged and is likely to vary between decision makers. While this problem is not isolated to our approach, the value of the rule of thumb and SDP formulation is that it forces decision makers to be explicit about the parameters in the decision process.

Other than *ad hoc* or arbitrary guidelines for declaring eradication, little attention has been directed to the problem of concluding eradication programmes of invasive species. While it is generally accepted that detection rates are imperfect, that species may persist in the seed bank, and the economic impacts of invasive species differ, the problem has never been formulated in the context of those variables. Instead the objective of an eradication programme is often to eliminate every potentially reproducing individual (Simberloff 2003) without much consideration of these factors or even on how the success of an eradication effort should be measured. Our model considers all these factors and tackles the problem of eradication from the perspective of whether continuing to survey is worthwhile. The problem then becomes one of minimizing the consequences (i.e. economic costs) of making the wrong decision (i.e. declaring eradication too soon, or continuing to search when the species is already eradicated). The decision support tool described in this paper enables an analysis of the decision trade-offs that result in optimal cost-effective solutions and improves decision-making for inferring eradication. Our approach only considers decisions based on the eradication of a single species rather than management directed at eradicating multiple invasive species concurrently. This provides a fertile avenue for future work. While we have developed this approach for invasive plants, the approach is general enough that it can be applied to any invasive species. It could also be used for decisions to move to a less costly post-eradication monitoring programme, or for releasing a species from quarantine. The approach is also useful for a wide range of surveys, including those directed to monitoring questions that infer extinction of threatened species.

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