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Plant extirpation at the site scale; implications for eradication programmes

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(A) **ABSTRACT**

Aim To identify the relative importance of commonly available site and species factors on the probability of extirpating a plant species at the site scale.

Location Australia

Methods We reviewed the plant eradication literature and listed the factors commonly cited as influencing eradication success. We then analysed a database of 408 site-scale extirpation attempts, across 17 species eradication programmes, by modelling the time until extirpation to determine the relative influence of these factors on the probability of extirpation, given time.

Results The most commonly cited factors influencing eradication success can be classified into two groups: those related to the 'organisation', being typically binary variables and amenable to management; and those related to the 'site/species', which typically were continuous values and usually beyond the control of the management agency. Detectability period, search distance, monitoring rate, infestation size, propagule longevity, time to reproductive maturity and previous eradication success all influenced the extirpation rate. Conversely, climate suitability, land use, and general accessibility (distance to nearest manager) were relatively unimportant. By relating the influential site/species factors to a time dependent model, managers and policy makers can explicitly estimate the probability of successful extirpation at a site, given a particular time horizon. These estimates can then be aggregated up to the species-scale to allow managers to set realistic goals regarding eradication timeframes and resource requirements.

Main Conclusions Our paper illustrates how the probability of extirpation at the site-scale can be quantitatively estimated and how these estimates can be used to inform decisions regarding broader species-scale eradication programmes. We expect that the use of such quantitative approaches to select better eradication targets will improve eradication success rates over time.

Keywords Bayesian statistics, biological invasions, eradication feasibility, extirpation, risk-return, survival analysis.

(A) **INTRODUCTION**

Invasive alien species represent a significant management problem to economies and natural environments the world over (Vitousek *et al.*, 1996; Mack *et al.*, 2000; Pimentel *et al.*, 2005). With increasing globalisation and free trade, record volumes of passengers and goods are being transported between countries, providing biological organisms with an unprecedented opportunity for long-distance dispersal (Dalmazzone, 2000; Hulme, 2009). Rates of biological invasion have consequently increased, further growing the number of species for which management action may be warranted (Fridley *et al.*, 2007; Ricciardi, 2007).

Once a species has naturalised in an area, eradication (being the elimination of every individual of a species from a geographic area that is sufficiently isolated to prevent reinvasion (Newsom, 1978)) is often considered to be the most cost-effective method of reducing its future impact (Harris *et al.*, 2001; Wittenberg & Cock, 2001). Over the past twenty years, the number of eradication projects being attempted has steadily increased (Gardener *et al.*, 2010; Howell, 2012; Pluess *et al.*, 2012). A key assumption of such attempts is that eradication is 'feasible' with a 'realistic' amount of resources (Rejmanek & Pitcairn, 2002; Panetta, 2009).

Research into factors that influence eradication feasibility of invasive plant species has evolved considerably since Rejmanek & Pitcairn's (2002) seminal manuscript. Due to the long-term nature of plant eradication programmes, initial attempts at estimating eradication feasibility were predominately heuristic, using knowledge gathered from either a small selection of prominent case studies (Simberloff, 2003; Panetta & Timmins, 2004) or purely expert judgement (Cunningham *et al.*, 2004). Research effort then turned to using theoretical approaches such as population models (Cacho *et al.*, 2006) and bio-economic optimisation (Cacho *et al.*, 2007) to estimate likely success rates.

Only since Gardener *et al.* (2010) have larger datasets of eradication attempts been quantitatively analysed. The most recent efforts to model eradication success have used empirical methods to analyse plant eradication attempts (Howell, 2012; Pluess *et al.*, 2012). In these cases the authors used regression techniques to link biological factors with eradication success described as a binary (success / failure) eradication outcome at the species-scale. However, whilst Pluess *et al.* (2012) were able to replicate the initial finding of Rejmanek and Pitcairn (2002) that infested area was an influential factor, neither found empirical support for the other hypothesized factors.

The failure of these studies to support their initial hypotheses, coupled with their relatively low rates of eradication success (~10-20 %) (Gardener *et al.*, 2010; Howell, 2012), has contributed towards a creeping pessimism that the eradication of plant incursions is not 'feasible' except in highly constrained circumstances (Gardener *et al.*, 2010; Panetta & Cacho, 2012; Renteria *et al.*, 2012). However, the findings of these studies may have been influenced by highly variable management practices (Howell, 2012) and by treating ongoing eradication programmes as failures (Gardener *et al.*, 2010; Pluess *et al.*, 2012), despite the fact that many of the species could not have been eradicated within the timeframe analysed.

Here we take a different approach by considering eradication success to be influenced by not only site and species factors, but also time. Using a similar type of dataset to both Rejmanek and Pitcairn (2002) and Howell (2012), we use failure-time analysis (Muenchow, 1986; Kleinbaum & Klein, 2012) to estimate the probability of site-scale extirpation (being local, rather than global, elimination (Panetta, 2007)) as a function of the proposed site/species factors and time. By analysing extirpation at the site scale, complications in achieving eradication caused by issues such as inadequate delimitation can be controlled for and site-scale factors such as land use, climate match and monitoring rate can be incorporated. We minimise arbitrary variation in the dataset (sensu Pluess *et al.*, 2012) by using data from a single agency, thus providing an opportunity to hold organisational factors constant and identify the relative influence of the site and species factors on extirpation success.

(A) **METHODS**

To build an empirical model of extirpation success, we first reviewed the literature to identify factors thought to influence eradication feasibility. We then collated site extirpation information for each eradication attempt undertaken by an Australian state biosecurity agency between 1988 and 2008. Finally, we analysed a number of statistical models relating time to extirpation (or abandonment) with the biological variables thought to influence eradication success. Details of these steps are given below.

(B) **Review and selection of explanatory variables**

An extensive review of the eradication literature was undertaken using a number of internet based search tools including ISI Web of Science, Scopus and Google Scholar. Search terms included: erad*, feas*, invas*, weed*, exotic*, noxious*, success*, fail*, Panetta, Simberloff and evaluation. A total of twelve articles and reports contained factors proposed to influence eradication feasibility. From the complete list, twelve site or species-scale factors were chosen for use in the analysis on the basis of their frequency within the literature and availability of accurate data (Table 1). We ensured the factors represented the full range of variables discussed in the literature and included measures of detectability, fecundity and control logistics (Bomford & O'Brien, 1995; Panetta & Timmins, 2004).

(B) **Data collection**

The Victorian Department of Environment and Primary Industries (VDEPI) is the government agency responsible for overseeing control and eradication of invasive plants and animals in the State of Victoria, Australia. Government intervention can include declaring species as 'noxious weeds' under the *Catchment and Land*

Protection Act (1994) (CaLP). VDEPI is required to take all reasonable steps to eradicate those noxious weeds declared in the category of 'State Prohibited' from all land in the State. This legislative framework is very similar to that of the Californian Department of Food and Agriculture (CDFA) as described by Rejmanek and Pitcairn (2002).

The CaLP Act implicitly requires consistency in the organisational factors listed in Table 2 across eradication attempts by mandating responsibilities on the State. As such, arbitrary variation in the dataset caused by different approaches to management (sensu Howell, 2012; Pluess *et al.*, 2012) is minimised, providing an ideal opportunity to identify the relative influence of site and species-based factors on extirpation success (Panetta, 2009). In addition, many species targeted for eradication by VDEPI were chosen well before even the earliest research into eradication feasibility, therefore, any possible bias arising from analysing only sites already considered 'feasible' (within current understanding) is also minimised.

To date, VDEPI has successfully extirpated 65 of the 408 known infestation sites of State Prohibited Weeds (SPWs) across Victoria. Many additional sites are in the 'monitoring phase' (Panetta, 2007), with extirpation only declared by VDEPI once monitoring has not detected the species for a period greater than its seed longevity. Complete information for the 408 infested sites was obtained for eradication attempts undertaken by VDEPI on 17 species of 'State Prohibited Weeds' between 1988 and 2008 (see Table 3 for species list). The numbered variables are those used in our analysis.

For each infested site, VDEPIs Integrated Pest Management System provided information on: latitude, longitude, species, date first detected, (1) net infested area – defined as the area requiring actual treatment (data range: 0.0001-150 ha), percent cover, (2) monitoring rate, and current status of the infestation. VDEPI also provided habitat match data generated in the CLIMATE program (Pheloung, 1996) for each species, details of which can be found in Weiss and McLaren (2002).

The data were then imported into ESRI ArcGIS 9.3 (ESRI, 2008) where (3) land use, (4) CLIMATE match and (5) distance to the nearest management office were determined for each site. Land use was classified according to version six of the Australian Land Use and Management Classification (ALUM) System (Bureau of Rural Sciences, 2006).

We then generated alpha-hulls in the R software environment for statistical computing and graphics (R Core Team, 2013) to estimate gross infested area of the delimited infestations (sensu Panetta & Lawes, 2005). Alpha-hulls were chosen as they provide a more accurate estimate of a species' range than minimum convex polygons (Burgman & Fox, 2003). Analyses were undertaken using the R packages '*tripack*' (Renka *et al.*, 2009) and '*spatialkernel*' (Zheng & Diggle, 2006), the Delaunay triangulation method and an alpha value of 3. Statistics for each of the alpha-hulls were recorded with the values for (6) gross infested area – defined as the total area needed to be searched for a species and (7) number of known other sites of that species appended to the data table for each site.

Finally, demographic parameters for each species were obtained using refereed literature and the field experience of the authors. For each species we determined: (8) propagule longevity, (9) time to reproductive maturity, (10) annual period during which the species is detectable (i.e., has above ground parts) prior to seed set, (11) search distance (sensu Cacho *et al.*, 2006) immediately prior to flowering and (12) whether (or not) the species was known to have been eradicated elsewhere (globally). Propagule longevity could not be reliably determined from the literature for *Nassella charruana* (Arechav.) Barkworth and *Malvella leprosa* (Ortega) Krapov., and we applied the principles of Bekker et al. (1998) to obtain data from related taxa *Nassella neesiana* (Trin. & Rupr.) Barkworth and *Sida spinosa* L. respectively.

(B) **Model construction**

We used failure-time analysis, coupled with Bayesian hierarchical regression, to test the relationship between model variables and extirpation success at each site. Failure-time analysis relates the time to an event occurring (failure-time) with any combination of explanatory factors (Hosmer & Lemeshow, 1999; Kleinbaum & Klein, 2012). In our model, 'failure' is the point at which extirpation at the site was declared by VDEPI and 'failure-time' was the time that had elapsed since commencing the extirpation attempt (data range: 2-21 years).

When an extirpation programme at a site is ongoing (or abandoned), the data were right censored (Muenchow, 1986). Sites were only abandoned (Table 3) when the species present at the site was subsequently discovered at too many other sites, such that eradication of the species from Victoria was deemed too costly. Thus, all sites of a species were abandoned even though site-level extirpation had been achieved at individual sites (Table 3).

Failure-time analyses are defined by how the rate of failure (in this case extirpation) varies with time, conditional on survival to that time. This is termed the hazard function. However, as there is only a small body of evidence describing how the probability of eradication varies with time, we were unsure about the form of hazard function to use. Three different models of time to extirpation were, therefore, fitted as part of the model building process, with each implying a different hazard function.

In the simplest case, we used the exponential distribution of time to extirpation, therefore implying that extirpation occurs at random (*i.e.* at the same rate) throughout time. In this case the instantaneous potential for failure (achieving extirpation) remains the same, regardless of the time elapsed. This is referred to as a constant hazard rate. Under this model, time to extirpation has a probability density function:

$$f_E(t) = r\exp(-rt) \qquad \text{(eqn 1)}$$

where t is time and r is the reciprocal of the mean time to extirpation; we refer to the parameter r as the "extirpation potential" of a particular scenario. The model for r is presented in equation 6 below.

The Weibull distribution generalizes the exponential distribution but allows the hazard rate to vary over time as a power function of the time since commencement, therefore implying that the rate at which extirpation occurs either increases or decreases over time. It has the probability density function:

$$f_W(t) = \lambda v t^{v-1}\exp(-\lambda t^{v}) \qquad \text{(eqn 2)}$$

where the hazard function is either increasing ($v>1$) or decreasing ($v<1$) over time t, with the shape parameter v estimated during the model fitting. Given a particular value for v, the parameter λ controls the mean time to extirpation ($1/r$) such that $\lambda = \Gamma(1+1/v)r$, where $\Gamma()$ is the gamma function.

The final model type, the log-normal distribution, also allows the hazard rate to vary over time but unlike the Weibull hazard function it implies that the rate of extirpation first increases then decreases over time. It has the probability density function:

$$f_L(t) = \exp(-(\ln t-\mu)^2/(2\pi/\sigma^2)) \,/\, (t\sqrt{(2\pi\sigma^2)}) \quad \text{(eqn 3)}$$

$$\mu = -\ln(r) - 1/2\sigma^2 \quad \text{(eqn 4)}$$

where μ and σ are the mean and standard deviation respectively of the corresponding normal distribution, both of which are estimated during model fitting (μ is estimated via its relationship to r).

The probability of extirpation within time t is then the definite integral of the relevant density function (equations 1 to 3):

$$F(t) = \int_0^t f(u)du \quad \text{(eqn 5)}$$

In these models, the probability of extirpation increases towards an asymptote of 1. That is, we assumed that species would be extirpated from sites eventually with enough effort. To check this assumption, we also conducted alternate analyses where the probability of extirpation increased to an asymptote less than one. The estimated asymptote in these analyses was close to one (data not shown), and the estimated regression coefficients similar to the model based on eqn (5), so we only report results of the simpler models.

For each model of time to extirpation, the log of the 'extirpation potential' r (the reciprocal of the mean time to extirpation) of species i at site j was assumed to be a linear function of the explanatory variables, such that:

$$\ln(r_{ij}) = a + b_1 X_{1j} + \ldots + b_n X_{nij} + c_i \qquad \text{(eqn 6)}$$

where X_{1j} is net infested area (ha), X_{2j} is monitoring rate (pa), X_{3j} is land use class (ALUM), X_{4ij} is CLIMATE match score (0-4), X_{5j} is distance to nearest management office (m), X_{6j} is gross infested area (ha), X_{7j} is number of other sites, X_{8i} is propagule longevity (years), X_{9i} is time to reproductive maturity (years), X_{10i} is annual period of detectability prior to seed set (months), X_{11i} is search width (m), X_{12i} is whether the species has been eradicated elsewhere (1 when yes, 0 when no), and c_i is a species random effect. This random effect was assumed to be drawn from a normal distribution with a mean of zero and an estimated standard deviation.

The parameters v, a and b_1 to b_{12} were estimated from the data by fitting the models in the OpenBUGS software package (Lunn *et al.*, 2009) using a Bayesian analysis. Uninformative priors were assigned to the model parameters to ensure the data had the greatest impact on the posterior distribution. These priors were normally distributed with a mean of zero and a variance of 10^6 for the regression coefficients and uniform between zero and 100 for the shape parameter (v) and standard deviation (σ). Each model was estimated using three chains of 1,000,000 samples after an initial burn-in of 10,000 samples. Convergence of the Markov chains was evaluated visually.

(B) **Model evaluation and selection**

Model performance was evaluated within an information theoretic framework using the DIC (Deviance Information Criterion) values generated by the OpenBUGS package (Lunn *et al.*, 2009). The full model (containing all explanatory variables) was used as a baseline for comparison, with reduced combinations evaluated stepwise for their effect on the model's DIC. Performance of the reduced model combinations was tested until further removal of any explanatory variables resulted in a decline in model performance. A total of 78 different model combinations were evaluated, consisting of 26 combinations for each of the three hazard functions.

To understand the relative influence of the explanatory variables on extirpation probability over time, we used the best performing model to predict $F(t)$ whilst independently varying the input variables across the range collected by VDEPI. We used a 2 hectare infestation of *Carduus nutans* L. as an example, with input values: net infested area of 2 hectares; CLIMATE match at the sample mean (3); detectability period of 12 months; detection distance of 15 metres; distance to nearest manager at the sample mean (30 km); propagule longevity of 12 years; monitoring rate at the sample mean (1 pa); time to reproductive maturity of 1 year; and known to have been eradicated elsewhere (η=1). All scenarios were run concurrently in OpenBUGS.

(A) **RESULTS**

(B) **Progress towards extirpation**

The VDEPI database contained 408 infested sites, 65 of which were successfully extirpated, 138 abandoned and 205 ongoing when the data were exported on 07/05/2009. The 17 species targeted, and their respective success rates are in Table 3. *Salvinia molesta* D. S. Mitch., *Acacia karroo* Hayne and *Eichhornia crassipes* (Mart.) Solms were the most frequently extirpated species with success rates of 100%, 75% and 67% respectively. Conversely, species in the genera *Nassella* (Trin.) E. Desv. and *Hieracium* L. were least frequently extirpated, with no single infestation extirpated by VDEPI. In total, 10 of the 17 species attempted had been successfully extirpated from at least one site (Table 3).

(B) **Selection and classification of the proposed factors**

The literature review identified twelve publications that proposed factors influencing the feasibility of eradicating invasive plant species. Excluding the detailed variables used in the population modelling of Cacho *et al.* (2006), at least 25 separate factors could be identified, which were then broadly grouped as either 'organisational' or 'site/species'. Organisational factors were typically binary, with a yes/no outcome, but within the control of the management agency (Table 2). In contrast, site scale factors were almost exclusively continuous and directly measurable, but outside control of management (Table 1).

The influence these factors had on eradication success differed between the two groups. Organisational factors were typically described as having an absolute effect on eradication success, with a 'no' response for any variable making the species 'unsuitable' for eradication (sensu Bomford & O'Brien, 1995; Myers *et al.*, 2000; Panetta & Timmins, 2004). Conversely, site and species factors were typically described as having a cumulative effect, with each factor either positively or negatively contributing to the probability of success, but not absolutely linked to it. Many of these factors were only described generally in the literature and some additional interpretation was required to complete their descriptions in Table 1.

(B) **Analysis and selection of the underlying hazard function**

A total of 78 different model combinations were evaluated, consisting of 26 combinations for each of the three hazard functions (exponential, Weibull and log-normal). The best performing combinations of explanatory variables (those having the lowest DIC) were identical for the log-normal and Weibull models as was the direction and relative size of their coefficients. On the basis of this similarity we disregarded the log-normal models, given their increased computational demands and the extensive use of Weibull models in failure-time analyses (Kleinbaum & Klein, 2012).

In each of the best performing Weibull models the posterior estimate of the Weibull shape parameter ν (equation 2) was 3.3±0.3 (supplementary material) clearly indicating that the rate of extirpation (the hazard rate) increased with time. The exponential distribution is a special case of the Weibull distribution with $\nu = 1$ (Kleinbaum & Klein, 2012), which allowed us to also disregard the exponential models and select the 'increasing' Weibull distribution as the best performing model relating time to extirpation success.

(B) **Evaluation of the factors influencing extirpation feasibility**

We selected the best performing Weibull model using the DIC scores generated by OpenBUGS (Lunn *et al.*, 2009). The best performing model included nine 'site/species' factors. Previous eradication of the species, detectability (annual period of detectability and species' search distance) and monitoring rate all had a positive influence on the rate of extirpation, decreasing the predicted mean time to extirpation. Conversely, an increase in net infested area, propagule longevity and time to reproductive maturity all negatively influenced the probability of success (Table 4). The estimated model coefficient for each parameter is included in the supplementary material.

We created an example scenario using the best performing model to illustrate the influence of the model variables on the predicted probability of extirpation given time. The example scenario of a two hectare *Carduus nutans* L. infestation had an estimated 93% probability of being extirpated in 15 years, with a 95% credible interval of 48-100% (Fig. 1). Mean time to extirpation was estimated at approximately 9 years, with a 95% credible interval of 5-16 years.

By varying a single explanatory variable in the *C. nutans* scenario over the range observed in the dataset, whilst holding the others constant, we were able to explore the relative influence of each explanatory variable. The detection distance of the species (see Table 4) had the largest effect, altering the mean time by up to 14 years across the range of detection distances sampled. Predicted mean time to extirpation decreased by more than 11 years in this scenario if the species had been eradicated elsewhere (Fig. 2). In contrast, net infested area and propagule longevity had moderate negative effects on the probability of extirpation given time. In both instances, varying the input could alter the mean time to extirpation by up to five years (Fig. 2). The relative influence of each of the model variables is shown in Table 4 and Fig. 2.

(A) **DISCUSSION**

By assuming, reasonably, that extirpation probability is time dependent we have successfully quantified the site and species-scale factors that affect extirpation success (Fig. 2). This is the first time that field data have verified the hypothesized effects. The relationships identified support those previously reported (Bomford & O'Brien, 1995; Myers *et al.*, 2000; Simberloff, 2003; Panetta & Timmins, 2004). Understanding the influence of these factors on extirpation success allows us to predict the efficacy of eradication scenarios more reliably.

(B) **Relating eradication success factors to time**

Our partitioning of factors into 'organisational' or the individual infestation 'site/species' interaction builds on the concept first proposed by Panetta and Timmins (2004) that factors could be partitioned into those that affect 'suitability' and 'feasibility' respectively. This subtle but very important distinction is integral to our analysis, and indeed any eradication programme, as it explicitly acknowledges that eradication feasibility is influenced not only by biological factors related to the species, but also socio-political, economic and operational ones (Panetta *et al.*, 2011). However, only a few qualitative analyses of these organisational factors have been published (Myers *et al.*, 2000; Genovesi, 2005; Simberloff, 2009) and this is clearly an area that would benefit from further research.

Even when the organisational factors are consistently met, plant eradication programmes often take decades (Mack & Lonsdale, 2002; Panetta & Lawes, 2005; Panetta *et al.*, 2011). For this reason, simply analysing percentage success rates at an arbitrary time (sensu Gardener *et al.*, 2010) fails to recognise that eradication of many of the infestations could not reasonably be expected in the timeframe analysed (given the factors listed above). Instead, we adopt the recommendation of Bomford and O'Brien (1995) that eradication probability needs to be expressed in terms of a particular time frame. So although VDEPI has a low raw percentage success rate (16%), we are more interested in extirpation success as it relates to the time elapsed since the extirpation attempt commenced.

Using failure-time analysis (Hosmer & Lemeshow, 1999; Kleinbaum & Klein, 2012), we were able to link time with extirpation success using a Weibull hazard function. In each of the best performing Weibull models, the posterior estimate of the shape parameter v (equation 2) was 3.3±0.3 (supplementary material). When the shape parameter is >1, the rate of extirpation (the hazard rate) increases as a power function of the time since the extirpation attempt commenced (McCarthy, 2007). This supports both our hypothesis that the rate of extirpation increases with time and the theoretical probability curves developed by Panetta *et al.* (2011). It is also consistent with the extensive use of Weibull models in failure-time analysis (Kleinbaum & Klein, 2012).

(B) **Site and species based success factors**

Of the factors ultimately considered in our analysis, those most frequently mentioned in the literature (Table 1; detection distance, net infestation size, propagule longevity, time to reproductive maturity, and annual period of detectability) also had the strongest influence on the mean time to extirpation (in that order). The notable exception was successful eradication elsewhere, which has not previously been proposed as a factor, but was the second most influential variable (Table 4). This suggests that biological factors not captured in the model, may also influence extirpation success. However, similar to invasiveness elsewhere being a strong predictor of invasiveness (Kolar & Lodge, 2001; Hayes & Barry, 2008), eradication elsewhere has limitations in its use as a predictive variable due to its bias against species for which eradication hasn't previously been attempted.

Detection distance (Cacho *et al.*, 2006; Cacho *et al.*, 2007) had the largest effect on the mean time to extirpation (Table 4 and Fig. 2) reflecting the implicit requirement to find all individuals to achieve extirpation. As illustrated by Panetta *et al.* (2011), detection distance is directly linked to the progression of sites from the active to monitoring phase (Panetta, 2007), achievement of which was the key challenge for recently abandoned Australian national eradication programmes for branched broomrape (*Orobanche ramosa* L.) and chromolaena (*Chromolaena odorata* (L.) King and Robinson).

Monitoring rate was the only 'site' factor related to management that correlated with extirpation success (Fig. 2). This finding supports the conclusions of Howell (2012) who hypothesised that extremely low monitoring rates in many of his study sites was the primary cause of failure to eradicate. Repeated monitoring of a site within a season increases the likelihood of finding the last hard to detect individuals and, in our scenario, could halve the mean time to extirpation (Fig. 2). We consider this to be a very important message for management agencies. Eradication is not simply about ongoing, ad-hoc, control with an indefinite goal of eradication (Bomford & O'Brien, 1995).

(B) **Predicting eradication feasibility**

By identifying that probability of extirpation should be linked to a time horizon and then understanding which factors influence extirpation rate, we are able to estimate extirpation probability given a set of infestation variables. In our example scenario, the model estimated a 93% probability of extirpation in 15 years (Fig. 1) which is reasonable given our experience with this species and its propagule longevity of twelve years. However, estimating extirpation probability is just one step toward estimating a species' broader eradication probability, which in itself is just one step towards deciding whether (or not) to attempt eradicating the species at all. Extirpation probability (and its associated timeframe) therefore, needs to be considered in conjunction with variables such the perceived risk of the species and the cost of intervening in order to improve efficiency (Panetta, 2009).

An additional benefit of using a Bayesian approach is that the credible intervals also explicitly represent the uncertainty in our estimates (McCarthy, 2007). The wide credible interval, even in this relatively straightforward example (Fig. 1), reflects the relatively low accuracy of estimates of extirpation rates, but importantly communicates a message of long-term commitment and no guarantee of success. For decision makers, understanding this uncertainty *a-priori* allows for realistic goal setting and consequently, the allocation of adequate resources. In effect, by understanding the influence of the infestation factors, it is easier to manage the organisational ones.

We expect that, as more eradication programs mature, the relative importance of the biological variables will become better understood. A larger set of successfully extirpated sites will allow for categorical variables such as land use to be described in more detail and also for more complex interactions between model variables. Other possible extensions include modelling the time to 'monitoring' (e.g. the conclusion of the active treatment phase) to better estimate treatment costs or to include a lower time bound based on propagule longevity. These may lead to simpler 'rules of thumb'. In addition, we will be able to validate the predictions made by this model against attempts that were ongoing at the time of the data collection, which should further refine the estimates of the regression coefficients in the model.

(A) **CONCLUSIONS**

Eradication is difficult and managers and scientists are right to question the likely success rates of eradication programmes. However, rather than concluding that eradication is not 'feasible', it is vital that managers understand the relative influence of different factors on eradication success and design their eradication programmes with them specifically in mind. We propose three recommendations for improving eradication success rates.

(1) All programmes should have realistic, time-based eradication objectives. Eradication is unlikely to occur in any time period less than the propagule longevity of the species and, as discussed above, in many cases may take decades. Identifying the likely time required *a-priori* allows policy makers to direct investment towards cases where eradication is likely. Within a constrained budget, this will maximise the reduction in future impacts, by preventing resources being wasted on attempts that are unlikely to succeed.

(2) The approach to achieving eradication should be suitably aggressive. Our results clearly indicate a large influence of both detectability and monitoring rate on extirpation success (Table 4). This finding implies that without sufficient effort, success rates will be lower; similar to the on-ground experiences of Howell (2012). Restating our earlier conclusion, the equivalent intensity of effort required to achieve eradication is far greater than that required for conventional, ongoing 'control/management'.

(3) Managing the 'organisational factors' should be considered before commencing an eradication attempt. Our findings, when viewed in conjunction with

the findings of Gardener *et al.* (2010) and Howell (2012), further support the original hypotheses of Bomford and O'Brien (1995) and Panetta and Timmins (2004) that these factors must be managed for eradication to be successful.

Our paper illustrates how the probability of extirpation at the site-scale can be quantitatively estimated. These estimates can be used to inform decisions taken at the species-scale prior to commencing new eradication programmes. We expect that the use of such quantitative approaches to select better eradication targets will improve eradication success rates over time.

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(A) **SUPPORING INFORMATION**

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

Appendix S1 WinBUGS model code for both analysis and prediction.

Appendix S2 Model coefficients for Appendix S1.

(A) **BIOSKETCH**

Aaron Dodd is a biosecurity policy analyst with a particular interest in the development of quantitative decision support tools. He works across the management spectrum from on-ground managers through to applied researchers and policy makers, capturing the unique insights that each discipline brings to biosecurity.

Author contributions: A.D, N.A, M.B and M.M conceived the ideas; A.D collected the data; A.D and M.M analysed the data; and A.D led the writing

Table 1: Summary of the most commonly proposed 'site and species' factors predicting eradication feasibility with key references. Factors selected for use in the analysis (including their units) are shown.

Factor	Type	Categories / Units	Expected relationship	Used in analysis	Key references
Control logistics					
Net infestation size	Continuous	Measurement (ha)	Negative correlation	Yes	(Rejmanek & Pitcairn, 2002; Cunningham *et al.*, 2004; Woldendorp & Bomford, 2004; Cacho *et al.*, 2006)
Monitoring rate	Continuous	Count (pa)	Positive correlation	Yes	(Cacho *et al.*, 2006; Gardener *et al.*, 2010; Panetta *et al.*, 2011; Howell, 2012)
Land use	Categorical	ALUM Land Use Class*	Residential = high Environmental = low	Yes	(sensu Panetta & Timmins, 2004) * Bureau of Rural Sciences (2006)
Climate match of species with site	Categorical	0-5 Scale	Negative correlation	Yes	N/A
General accessibility	Continuous	Distance to nearest management office (km)	Positive correlation	Yes	(Cunningham *et al.*, 2004; Panetta & Timmins, 2004)
Gross infestation size	Continuous	Alpha-hull (ha)	Negative correlation	Yes	(Rejmanek & Pitcairn, 2002; Cunningham *et al.*, 2004; Woldendorp & Bomford, 2004; Cacho *et al.*, 2006)
Number of separate sites	Continuous	Count (n)	Negative correlation	Yes	(Mack & Lonsdale, 2002; Cunningham *et al.*, 2004; Panetta & Timmins, 2004; Woldendorp & Bomford, 2004)
Knowledge of current locations	Categorical	High, Medium, Low	Positive correlation		(Cunningham *et al.*, 2004)
Fecundity					
Propagule longevity	Continuous	Measurement (years)	Negative correlation	Yes	(Cunningham *et al.*, 2004; Panetta & Timmins, 2004)
Pre-reproductive period	Continuous	Measurement (years)	Positive correlation	Yes	(Cunningham *et al.*, 2004; Panetta & Timmins, 2004; Cacho *et al.*, 2006)
Vegetative reproduction	Categorical	Yes / No	Negative correlation		(Cunningham *et al.*, 2004; Panetta & Timmins, 2004)
Number of propagules	Categorical	High, Medium, Low	Negative correlation		(Cunningham *et al.*, 2004)
Detectability					
Annual period of detectability prior to seed set	Continuous	Measurement (months)	Positive correlation	Yes	(Myers *et al.*, 2000; Groves & Panetta, 2002; Cunningham *et al.*, 2004; Panetta & Timmins, 2004)
Detectability (search theory)	Continuous	Sweep width (m)	Negative correlation	Yes	(Groves & Panetta, 2002; Cacho *et al.*, 2006)
Time to detection	Continuous	Count (years)	Negative correlation		(Mack & Lonsdale, 2002; Simberloff, 2003; Cacho *et al.*, 2006; Simberloff, 2009)
General					
Eradication achieved elsewhere	Categorical	Yes/No	Positive correlation	Yes	N/A
Understanding of species biology	Categorical	High, Medium, Low	Positive correlation		(Simberloff, 2003, 2009)

Table 2: Summary of the most commonly proposed 'organisational' factors predicting eradication feasibility with key references.

Factor	Type	Categories	Key references
Must be an available control measure for the species	Categorical	Yes / No	(Myers *et al.*, 2000; Simberloff, 2003; Panetta & Timmins, 2004; Cacho *et al.*, 2006)
Sufficient allocation of resources	Categorical	Yes / No	(Myers *et al.*, 2000; Genovesi, 2005; Simberloff, 2009)
Sufficient enthusiasm of project leaders	Categorical	Yes / No	(Mack & Lonsdale, 2002; Simberloff, 2009)
Single agency must be responsible for eradication	Categorical	Yes / No	(Myers *et al.*, 2000; Simberloff, 2003; Genovesi, 2005; Simberloff, 2009)
Nil cultivation value	Categorical	Yes / No	(Panetta & Timmins, 2004; Simberloff, 2009)
Prevention of reinvasion	Categorical	Yes / No	(Myers *et al.*, 2000)

Table 3: List of plant species and their respective success rate for which VDEPI has undertaken eradication campaigns.

FAMILY **Species**	**Success (%)**	**Eradicated (n)**	**Abandoned (n)**	**Ongoing (n)**	**Total (n)**
ASTERACEAE					
Carduus nutans	14	6	37		43
Centaurea nigra	11	6	49		55
Hieracium aurantiacum ssp. carpathicola	0			23	23
Hieracium praealtum subsp. bauhinii	0			7	7
Hieracium spp.	0			2	2
Iva axillaris ssp. robustior	0			1	1
EQUISETACEAE					
Equisetum spp.	25	11		33	44
FABACEAE					
Acacia karroo	75	6		2	8
Alhagi maurorum	2	1		46	47
Prosopis spp.	41	7		10	17
MALVACEAE					
Malvella leprosa	2	1	52		53
POACEAE					
Nassella charruana	0			56	56
Nassella tenuissima	0			5	5
POLYGONACEAE					
Fallopia japonica	14	1		6	7
Fallopia sachalinensis	0			3	3
PONTEDERIACEAE					
Eichhornia crassipes	67	22		11	33
SALVINIACEAE					
Salvinia molesta	100	4			4
Total	**16**	**65**	**138**	**205**	**408**

Table 4: Relative effect sizes of the factors selected for use in the analysis. The categorisation of effect sizes was “+/-“ <5 year change in mean time to eradication, “++/--“ 5-10 years, and “+++/---“ 10+ years.

Factor	Units	Best Model	Effect
Control logistics			
Net infestation size	Hectares	Yes	Negative (--)
Monitoring rate	Count (pa)	Yes	Positive (++)
Land use	ALUM Class*	No	-
CLIMATE match	0-5 Scale	Yes	Negative (-)
Accessibility (distance to manager)	Kilometres	Yes	Positive (+)
Gross infestation size	Hectares	No	-
Number of separate land managers	Count	No	-
Fecundity			
Species' propagule longevity	Years	Yes	Negative (--)
Species' pre-productive period	Years	Yes	Negative (--)
Detectability			
Annual period of detectability	Months	Yes	Positive (+)
Species' search distance	Meters	Yes	Positive (+++)
General			
Eradication achieved elsewhere	Yes / No	Yes	Positive (+++)

*The ALUM classification was sourced from the Bureau of Rural Sciences (2006).

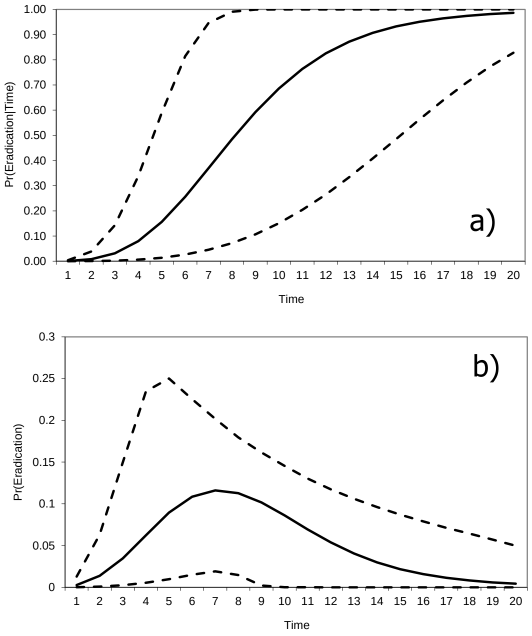

Figure 1: A predicted probability curve for an example extirpation target over time generated using 100,000 samples of the best performing Weibull hazard rate model. In this example the species is *Carduus nutans* L. (net infested area: 2 hectares, CLIMATE match: sample mean (3), detectability period: 12 months, detection distance: 15 metres, distance to nearest manager: sample mean (30 km), propagule longevity: 12 years, monitoring rate: sample mean (1 pa), time to reproductive maturity: 1 year, eradicated elsewhere: yes (1)). The solid line indicates the mean probability estimate and the dotted lines the 95% credible intervals. The cumulative distribution function (a) and the probability density function (b) are shown.

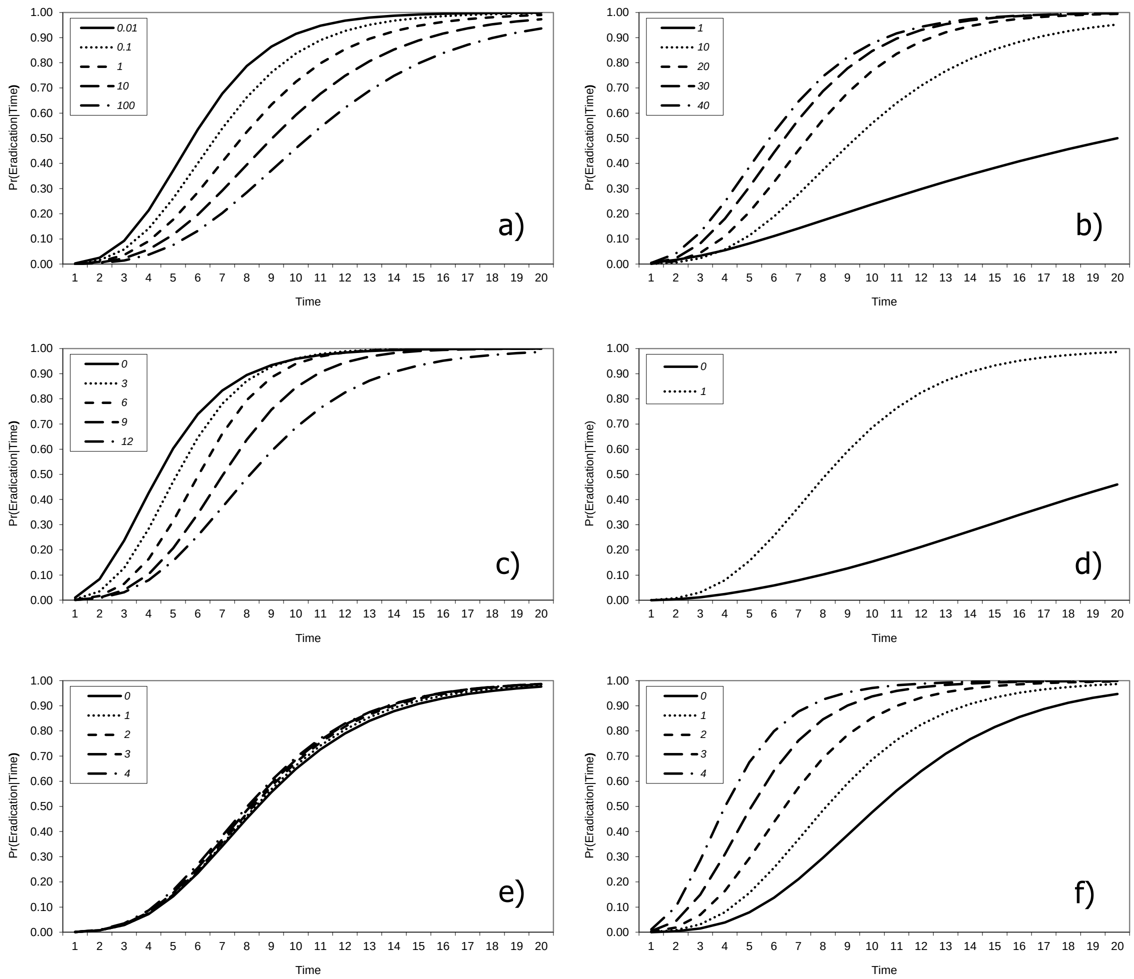

Figure 2: Predicted probability of extirpation over time for the example scenario used in Fig. 1 (a two hectare infestation of *Carduus nutans* L.) showing the effect of altering a single explanatory variable across its observed range whilst holding the others constant. Predictions were generated using 100,000 iterations of the best performing Weibull hazard rate model. Each line represents different values for the net infested area (a), detection distance (b), propagule longevity (c), eradicated elsewhere (d), climate match (e), and monitoring rate (f).