QUANTITATIVE DECISION SUPPORT FOR ERADICATION: A PRIMER

ANDREW GORMLEY, DEAN ANDERSON, AUDREY LUSTIG, CECILIA LATHAM, SIMON HOWARD, DAVID RAMSEY, MICHAEL SCROGGIE, MARCH 2021

COLLABORATION INNOVATION IMPACT

CENTRE FOR INVASIVE SPECIES SOLUTIONS

Arthur Rylah Institute for environmental research

Manaaki Whenua Landcare Research

The Centre for Invasive Species Solutions gratefully acknowledges the financial contribution from its members and partners to support its activities. Invasive Animals Limited governs and manages the Centre for Invasive Species Solutions.

This document was prepared by:

Andrew M. Gormley, Dean P. Anderson, Audrey Lustig, Cecilia M. Latham and Simon Howard
Manaaki Whenua – Landcare Research

David S.L. Ramsey, Michael Scroggie
Arthur Rylah Environmental Research Institute

This document should be cited as:

Gormley, A.M., Anderson D.P., Lustig, A., Latham C.M., Howard, S., Scroggie, M., and Ramsey D.S.L. (2021) Quantitative Decision Support for Eradication: A Primer. Manaaki Whenua – Landcare Research and Arthur Rylah Environmental Research Institute. Published by the Centre for Invasive Species Solutions, Canberra, Australia

www.invasives.com.au

ISBN Print: 978-1-925727-27-2

ISBN Web: 978-1-925727-26-5

Acknowledgements

Preparation of this primer and the described quantitative tools have been funded by Predator Free 2050 Ltd, Manaaki Whenua Landcare Research SSIF funding, and through the Centre for Invasive Species Solutions.

Cover Image by David Will, Island Conservation

CONTENTS

1 Introduction 3
  1.1 Spatial considerations: Extent; Management zones; and sampling units 3
  1.2 Principles of eradication feasibility 5
2 Initial assessment of the pest population 5
  2.1 Sampling frame 5
  2.2 Initial pest abundance estimate 6
  2.3 Spatial distribution 8
3 Planning eradication strategies 8
  3.1 Introduction 8
  3.2 Pest-Removal Simulation Models 9
4 Assessing Progress 10
  4.1 Estimating residual abundance 10
  4.2 Broadscale knockdowns 12
5 Proving Absence 12
  5.1 Principles of proving absence from zero detections 12
  5.2 Specifying the Prior 13
  5.3 Setting the target for declaring success 14
  5.4 Finding survivors: what is the worst-case scenario? 15
  5.5 Planning surveillance 16
6 Decision Support Tools 17
  6.1 Initial pre-eradication assessment tool 17
  6.2 Assessing eradication progress 19
  6.3 TrapSim: Predicting removal rates with trapping 21
  6.4 Proof of Absence 22
  6.5 Jess4Pests 24
7 Summary/Synthesis 25
8 References 26

1 Introduction

Eradicating a pest species from an area requires removing all individuals and simultaneously preventing reinvasion (Bomford & O'Brien 1995, Parkes et al. 2017). The list of international eradications is growing rapidly for diverse taxa (e.g. Ramsey et al. 2009; Ramsey et al. 2011; Samaniego-Herrera et al. 2013; Russell et al. 2016). New technologies and evidence-based strategies (Murphy et al. 2019; Nugent et al. 2018) are allowing for increasingly larger islands and mainland areas to be eradicated (Martin and Richardson 2019; Robinson and Copson, 2014; Anderson et al. in review).

Policy and management decisions associated with the eradication process are divided into four phases : (1) assessing feasibility, (2) planning control strategies, (3) assessing progress (and revising strategies), and (4) assessing and confirming absence of the pest species. Some decision making will be informed by experience, however often decisions will have to be made in the face of substantial uncertainty. Decision-support tools can provide insight and reduce uncertainty ultimately making the decision easier.

Quantitative decision support tools are simplified simulations of the system being studied. They help us understand the system and how its different components interact. A simple simulation model can provide insight on an ecological process or assess the likelihood of success of a management activity. Such models are invaluable to land managers and can help guide them in their decision-making.

In this primer we describe the phases of the eradication process and the management decisions that must be made. We focus on how quantitative models can help guide/inform the decision makers, and the data and parameters that need to be considered for these. The intent of this primer is to provide land managers with a general guidance on quantitative methods that can aide in achieving pest eradication. Further, we describe and provide links to software tools that we have developed that are freely available for eradication managers to use to build a scientific foundation for decision making (see Section 6).

This primer is intended to be a dynamic document. Just as eradication operations should adopt an adaptive management approach (Holling, 1978; Walter, 1986), the primer will be updated as we advance our knowledge of eradication science, and new quantitative tools become available. For further information or assistance gaining access to modelling tools, contact the corresponding author.

1.1 Spatial considerations: Extent; Management zones; and sampling units

The operation and decision making of an eradication program should be structured spatially and temporally. This provides a consistent framework for modelling, resource allocation for action on the ground, and decision making. The structure is hierarchical with at least three levels (Figure 1). The 'extent' is the entire area over which the programme aims to achieve eradication. Nested within the extent are management zones, in which ground operations are organised and staggered over time if necessary. Sampling units are nested within management zones and are the spatial unit for modelling (e.g. population density or detection/removal effectiveness) to inform decisions at the levels of the management zones or the full extent. For relatively small-area eradications, such as rodent eradications from small offshore islands with aerial toxin drops (e.g. Samaniego et al. 2013), the entire extent can be controlled and surveyed in a short period of time. In this case, a single (notional) management zone can cover the entire extent.

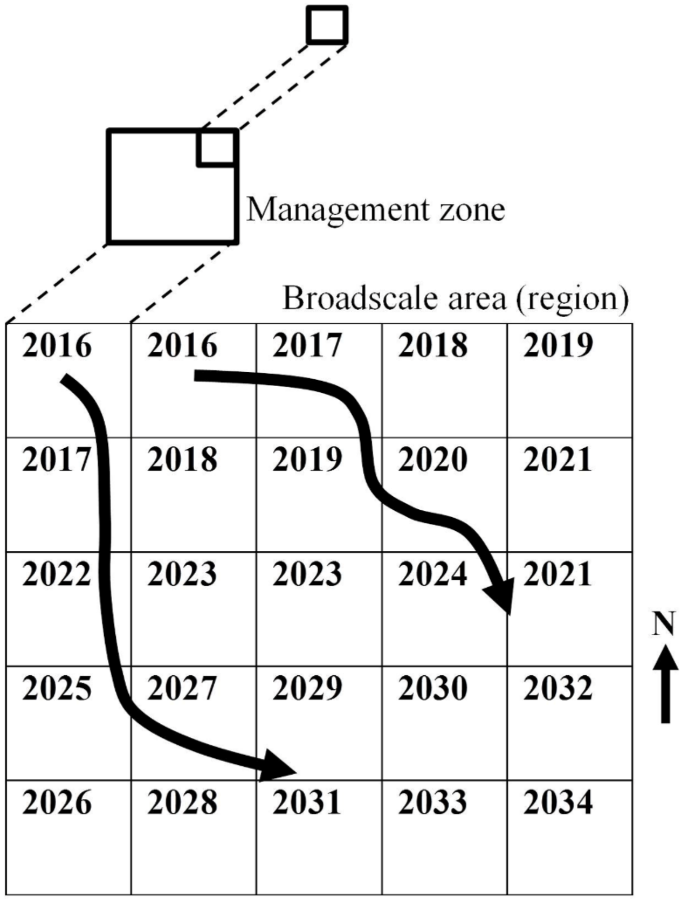

Figure 1. The spatial structure of a hypothetical broadscale eradication operation (Anderson et al. 2017). The smallest square is the sampling unit, which is nested in a management zone, which is nested in the full extent (broadscale area). The conceptual eradication begins in the northwest of the region in 2016 and finishes in the southeast in 2034.

When the eradication extent covers a very large area, and it cannot be entirely controlled or surveyed in a relatively short period of time, then the extent should be sub-divided into management zones and a two-stage broadscale eradication approach should be adopted (Anderson et al. 2017). Stage I occurs at the management zone level and corresponds to the removal of the pest population and surveillance to confirm freedom in the zone. The management zone is passed into Stage II when a high confidence in freedom is achieved, which allows reallocation of resources to other management zones. For clarity, we apply the term ‘freedom’ to refer to the complete removal of pests from a MZ, while the term ‘eradicated’ is reserved for the broadscale area of interest (a ‘region’ or entire country).

The control/surveillance operation advances progressively stepwise across the entire extent. In Stage II, surveillance within zones declared pest-free at stage I should continue so that any residual survivors are detected. Stage II surveillance is also used to estimate the probability of eradication across all zones (i.e. the entire extent).

1.2 Principles of eradication feasibility

Eradication of a pest species is appealing in that if successful, then there are no more costs associated with the detrimental effects of the pest nor costs associated with ongoing control activities (although it should be noted that there may be ongoing costs associated with preventing immigration and surveillance for potential incursions). However, eradication of an established species on any scale, large or small, is inherently difficult (Anderson et al. 2016, Cruz et al. 2009).

In order to successfully achieve eradication, there are three essential criteria that must be met: (1) rate of removal exceeds the rate of increase of the pest, (2) immigration is prevented, (3) all potentially reproductive individuals are put at risk (Bomford & O'Brien 1995). Three additional desirable criteria for determining whether eradication is preferred to sustained control are: (4) individuals can be detected at low densities, (5) cost-benefit analysis favours eradication over sustained control, and (6) there is socio-political support for eradication.

If it is reasonable to assume that criteria 2-6 above can be met, then the feasibility of eradication is then dependent on whether the removal rate of the pest is high enough to eliminate the population. The first stage in this process is having some understanding of the current population size and spatial distribution/extent of the pest. Knowledge of current population levels will inform the level of effort (and cost) required to obtain an effective pest removal rate.

Given an initial estimate of population size, a simulation model can be used to forecast the removal effort (e.g. number of devices, spacing, people days, frequency and duration of control activities) required to achieve eradication (Gormley and Warburton 2020; Anderson et al. 2016; Ramsey and Efford 2010; Ramsey et al. 2005; Glen et al. 2017; Lustig et al. 2019). These models require parameters related to the probability of removal of individuals, and can include additional complexity related to population growth, survivorship, movement behaviour and potential re-incursions, and landowner participation. The combined monetary and social costs of pest removal and subsequent surveillance to confirm eradication can be used to find the optimal effort required to achieve eradication as well as its likely total cost. Alternatively, if a fixed budget is assumed, the goal would be to determine whether eradication can be achieved with the chosen techniques within the defined budget. Information on the feasibility of eradication can therefore be important for determining whether an eradication should be attempted, or whether sustained control or containment would be a more viable option.

2 Initial assessment of the pest population

Prior to undertaking eradication activities an initial assessment of the pest population is advised to provide information that can be crucial for guiding eradication phase activities. Some guidelines for undertaking this initial assessment follow. Quantitative models exist to assess the abundance and distribution of a pest population, and a suite of statistical tools that will be freely available and user-friendly are being developed.

2.1 Sampling frame

The initial assessment of the abundance and distribution of the pest population can be done over management zone(s) or over the entire eradication extent. Either way, the extent needs to be divided into sampling units, which can be regular or irregular size plots that are contiguous and do not overlap.

The sizes of the sampling units are usually designed with the biology and underlying spatial distribution of the target species in mind, as well as the monitoring methods that will be used. Sampling units should be at least as large as the average home-range size of the target species to avoid possible edge effects. Ideally auxiliary information about each sampling unit will also be available (e.g. habitat type, topography). This information can be used as explanatory variables to predict how population abundance varies across the survey region. In addition, these auxiliary variables can be used as stratification variables to increase the precision of abundance estimates.

In order to use this plot-based sampling frame to estimate abundance, a number of assumptions need to be satisfied. Firstly, all individuals within a plot must be at risk of being detected by the chosen monitoring method. Secondly, it is essential that there be insignificant movement of individuals between plots. Ultimately, the objective of the initial population assessment is to gather information on the approximate size and spatial extent of the pest population to enable further decision support on the feasibility of eradication and the optimal allocation of resources. Further discussions around the design of surveys for abundance estimation can be found in (Thompson et al., 1998).

2.2 Initial pest abundance estimate

An initial estimate of the size of the pest population will enable a first estimate to be made of the likely costs associated with achieving eradication. It will also enable an initial evaluation of different monitoring techniques. Several techniques are available for estimating population abundance based on repeated sampling of unmarked individuals, plots or resightings of marked individuals. The method chosen will depend on both the type of monitoring device used to make observations and the ease with which it can be deployed. In general, sampling a pest population to obtain information on population size and/or distribution can be divided into count methods, abundance estimation based on marked animals and indirect methods (sections below).

Count methods

These involve counts of individuals using either visual methods (e.g. line transect sampling, point counts) or capture (e.g. trapping, hunting). Direct counts of individuals are suitable for estimating population size. The most accurate estimation method is a total count, in which every individual in the population or sampling unit is counted. However, it is usually impossible or impractical to do this, so an incomplete count is usually used. Statistical methods are then used to correct the incomplete count for imperfect detection of individuals. Here we concern ourselves primarily with data generated from incomplete counts. An incomplete count is related to a complete count (the estimated actual population size) by the equation

$$\hat{N} = \frac{C}{\hat{p}}$$

where $\hat{N}$ is the estimate of actual population size, C is the number of individuals in the incomplete count, and $\hat{p}$ is the estimate of detectability (i.e. the proportion of the total population detected). There are three basic approaches for estimating the detectability parameter $\hat{p}$ and thus the size of a closed population (Borchers et al. 2010):

1 Use changes in the number of individuals detected as some feature of the survey changes (e.g. line transects, point counts).

2 Use changes in the number detections as individuals are progressively removed (e.g. removal methods, change in ratio methods).

3 Use the proportion of individually marked animals that are recaptured (e.g. mark-recapture methods).

Of these approaches, (1) is the easiest to implement as it only requires observations of the pest during sampling. Approach (2) requires removal of some of the pest population, which is likely to be more labour intensive and would usually be undertaken as part of the actual implementation of the eradication program. Approach (3) can involve physical capture and marking of individuals followed by observations of these marked (and unmarked) individuals. Physical marking can be quite labour intensive so modern techniques tend to rely on observations of unique natural markings (e.g. pelage patterns) to uniquely identify individuals (i.e. from remote camera images).

Several methods are available to estimate population size that use repeat count observations of a sampling unit. The most popular of these method is the binomial mixture (or N-mixture) model (J.A. Royle, 2004). Other methods utilise counts of individuals as well as the time of detection (Moeller et al., 2018; Nakashima et al., 2018), which are usually available from time-stamped camera images. An additional method records the distance of individual pests from the observer from a point or line and uses distance sampling methods to estimate population size (Howe et al., 2017; Thomas et al., 2010). Some of these methods have been implemented into the online tool designed for conducting an initial assessment of a pest population (**see section 6.1**).

Abundance estimation based on marked animals

A more robust and usually more precise estimate of population abundance can be obtained by marking individuals of the target species and then releasing them back into the population. Further sampling is then undertaken, identifying both marked and unmarked individuals. The most popular method of marking individuals does not require physical capture but recognises individuals by their distinctive physical markings or by genetic identification. If physical capture is used to mark individuals, it is advisable that GPS and/or radio telemetry collars be placed on individuals so that targeted removal can be undertaken if necessary. The use of GPS or radio telemetry collars (or both) has additional benefits as it provides estimates of space use by individuals, which can be used to help design an efficient removal strategy (e.g. Anderson et al. 2016; Gormley and Warburton 2020).

Indirect methods

Monitoring methods that yield data on the presence of one or more individuals, but not of the individuals themselves (i.e. scats, footprints, etc.) are indirect monitoring methods. These are commonly referred to as indices of abundance and are presumed to be a measure that is correlated with true abundance. These methods are appealing in that they are typically cheaper to implement than direct count or mark/recapture methods. Indices can be (a) presence/absence indices, or (b) relative abundance indices. Presence/absence indices (e.g. presence of sign) cannot usually be used to estimate population size but is more suited to estimating spatial distribution (i.e. occupancy). Imperfect detectability p of index surveys can also be estimated if repeat observations are made for each sampling unit so that the proportion of the sampled landscape occupied by the pest can be corrected for imperfect detection (MacKenzie et al., 2006). An extension of these occupancy models that posits a functional relationship between occupancy and abundance can be used to derive an approximate population size from presence/absence surveys (J Andrew Royle & Nichols, 2003), which may be useful in some circumstances.

Index surveys can also serve as an alternative method for detecting pest presence during the final stages of eradication activities. This can be useful when the primary method of pest removal becomes less effective at low population density due to low detectability (i.e. trap-shyness). Hence, having an alternative detection method(s) can be crucial for detecting the last few survivors of an eradication program. Hence, index surveys can safeguard against a change in detection efficiency that could occur towards the end of the removal phase. Information from presence/absence surveys can also be combined with count survey methods to make joint inference on estimates of population size (Chen et al., 1998).

2.3 Spatial distribution

An important component of the initial assessment is determining the spatial distribution of the pest species across the full extent. That is, how does pest density vary within and across management zones (Figure 1). Information about spatial distribution is important for designing a monitoring program that can provide population estimates that are unbiased and precise. Systematic sampling of all units across all management zones will rarely, if ever, be feasible. Therefore, a representative sampling regime must be devised. If the target population is approximately randomly distributed, then a monitoring program can use a simple random sample of the sampling units. However, clumped spatial distributions are better monitored using stratified random sampling to increase precision. In the latter case, habitat attributes will often be used to delineate strata. Using the data from stratified or random samples, statistical models can be developed to predict population abundance (or relative abundance) in sampling units and management zones that were not surveyed.

3 Planning eradication strategies

3.1 Introduction

Controlling a species at a landscape scale is inevitably an expensive endeavour (Cruz et al. 2009). The level of and duration of control depends on a number of factors, the main one being the overall management aims (eradication vs sustained control). In this primer we focus on eradication, however many of the same principles apply for sustained control and/or containment.

Given a goal of eradication, how do we decide on the best control strategy to achieve it? There are a wide range of control tools available, the choice of which depends on factors such as the habitat where target species occurs. In some areas, typically remote forested areas, aerial deployment of toxic bait is the preferred and sometime only viable method of pest control. In other areas, pest control is ground-based, consisting of either bait stations, live-trapping, kill trapping or some combination.

Even for a single control method, there are still many decisions that need to be made. For example, if kill-traps are to be used, the manager still must decide on a ‘trapping-regime’ including factors such as trap density (spacing between traps), trap-capacity (single vs multiple capture), checking interval (daily vs once a month) and duration (how long will traps be deployed).

3.2 Pest-Removal Simulation Models

One way of selecting an appropriate control regime is to use a computer model that simulates pest removal, which enables a quick comparison of the relative effects on pest abundance across a wide range of control options. Removal methods can include trapping, bait stations with toxin and hunter tracks (Anderson et al, in review). These models can be used to determine whether the level of effort necessary to achieve eradication is feasible. A common approach is to use a spatially-explicit model that can simulate the ground-based removal of individuals from a pest population (Glen et al. 2017; Lustig et al. 2019; Anderson et al. 2016).

The general approach assumes that removal devices are represented by georeferenced point locations within the area of interest, such as traps or bait stations. Hunter or dog tracks can be incorporated into this framework by discretising the movement tracks into points at a set distance interval (e.g. 50 m).

The model simulations are initialised by creating a starting pest population of a specified size/density and placed randomly in the landscape with locations corresponding to the home-range centres of individuals. Instead of simulating actual animal movements across the landscape, each animal is assumed to have a circular home range. Interactions between removal methods and pest animals are determined by two parameters. The first is g_0 (pronounced g-naught), which is the nightly probability of capture of an animal by a removal method located at the centre of its home range. The second is σ (pronounced 'sigma'), which is the standard deviation of the bivariate (circular) normal distribution (Efford 2004). The radius of the 95% circular home range is given by 2.45σ, which defines the area where an individual spends 95% of its time. Note that values of the g_0 and σ parameters will likely differ between species and habitats, and g_0 will also differ between removal methods. There may also be differences in these parameters due to additional factors such as season, population density and individual behaviour.

The nightly probability of each animal *i* being removed by device *j* is given by:

$$p_{ij} = g_0 \exp\left(\frac{-d_{ij}^2}{2\sigma^2}\right)$$

where d_{ij} is the distance between the home-range centre of the animal and the device location, or the point location of a hunter or dog. Animals that interact with devices or are shot by hunters are removed from the population. When simulating removal by trapping, traps that successfully capture individuals are turned off and are unavailable to capture other animals until the next scheduled trap checking period.

Other model structures (e.g. Lustig et al. 2019) differ slightly in that the probability of removal is defined at a sampling-unit level, rather than for each individual animal-device combination. In this case, the probability of removal is calculated as a function of device density (e.g. bait station density) in that sampling unit:

$$P_{rem} = 1 - e^{-2\pi g_0 \sigma^2 k \rho}$$

Where *k* is the number of days and *ρ* is the device density (per m^2). The sampling-unit structure above would also be suitable for estimating the effect of total search effort (e.g. by a hunter) within the sampling unit on the removal probability. This is achieved by a slight modification of the above:

$$P_{rem} = 1 - e^{-\theta k \rho}$$

Where θ is the removal rate per unit of search effort, k is the number of days and ρ is the total amount of search effort, per day, within the unit. Typically θ can be estimated from samples of removal and effort data, collected from at least three sampling periods (Gould & Pollock 1997).

Other components of population dynamics can also be included in the simulation models. For example, one method of incorporating in-situ reproduction is to simulate the number of new offspring born each reproductive period as drawn from a Poisson distribution with mean λ, given by:

$$\lambda = rMax \times N\left(1 - \left(\frac{N}{K}\right)\right)$$

where *rMax* is the maximum rate of increase, *N* is the current population size and *K* is the carrying capacity of the area. Similarly, features such as juvenile dispersal, immigration, and habitat-specific maximum densities can also be specified (Lustig et al. 2019).

These types of simulation models offer managers insights into the pest-removal process as well as allowing for sensitivity testing, i.e. how outcomes change depending on the values of species-specific parameters (e.g. g_0, σ, θ). This is particularly useful when there is likely to be substantial uncertainty around values for these parameters.

These individual-based (or agent-based) models have been applied to a variety of cases to help provide guidance on the effort required to achieve a desired level of pest removal, including control of mustelids and feral cats in Cape to City (Glen et al. 2017), possum eradication in Mahia Peninsula, and possum eradication in the Kaitake Ranges. The TrapSim model (**see section 6.1**) is a freely available and user-friendly online tool to help managers plan eradication strategies.

4 Assessing Progress

4.1 Estimating residual abundance

Consideration of the primary removal method is of great importance because the results will also be used to generate residual population abundance estimates. For valid estimates to be obtained, the primary removal method must be able to remove individuals at a rate faster than they can be replaced either by reproduction or immigration. This can be easily visualised using a cumulative catch curve (Figure 2), which plots the cumulative catch (removals) of individuals against the catch per unit effort (CPUE). The negative of the slope of this relationship is an estimate of the detection rate (also known as the catchability coefficient). If a clear negative relationship is not evident or if there is evidence of a flattening of the relationship (non-linearity), that suggests that the population might not be reducing at a rate high enough to achieve eradication or that the detection rate of individuals is declining. If this occurs, then alternative removal techniques need to be used. One problem with relying on the cumulative catch versus CPUE plot is that the relationship may suggest that all individuals have been removed, when in fact, eradication has not been achieved. This occurs because the relationship in Figure 2 assumes that detectability is constant for the duration of removal activities when in fact, the residual population is no longer susceptible to the removal method (e.g. they may be trap-shy and therefore never get caught, resulting in detectability declining to zero). Recognizing when this has occurred depends on the use of a monitoring protocol running in parallel with the primary removal method that is able to detect residual survivors (e.g. remote cameras or scat-detecting dogs).

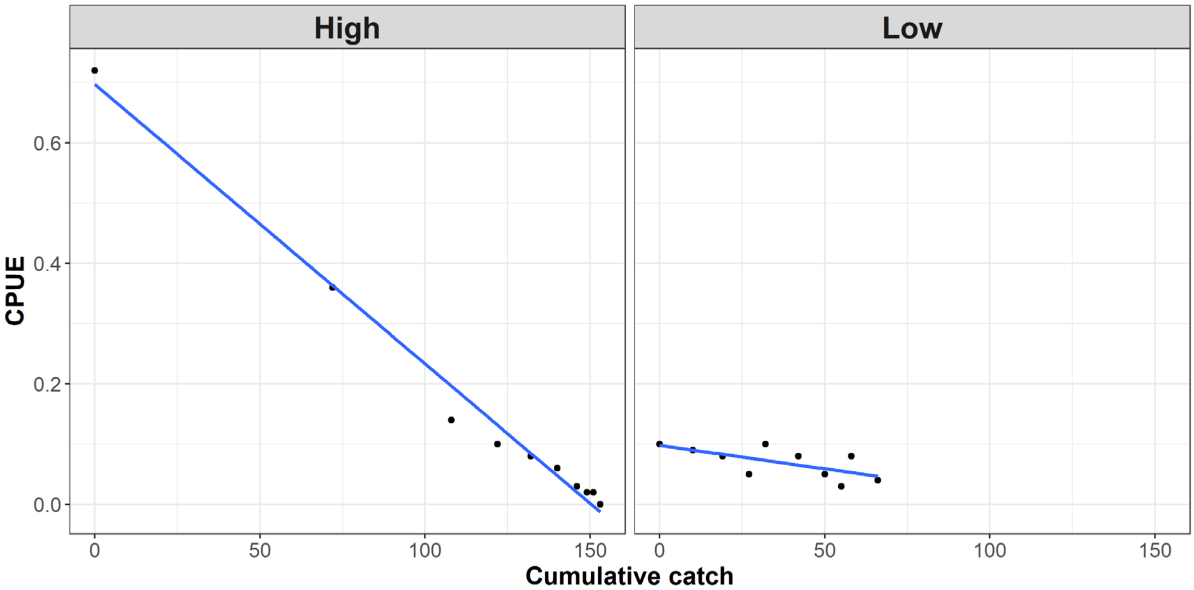

Figure 2. Plot of the cumulative catch (removals) of individuals vs the catch per unit effort for two hypothetical eradications with a high or low removal rate.

Once sufficient removal and monitoring data have been collected, analyses of these data can then be used to update the estimate of the residual population size as well as predict the amount of additional effort required to achieve eradication. In the latter case, if removal costs are known, predicted effort should be cost-effective relative to the probability of achieving eradication. Data from a minimum of three control sessions is usually required to generate an estimate of population abundance using removal data. The tasks undertaken to assess progress towards eradication will therefore involve:

- Estimates of residual population abundance per time unit, using the removal data as well as data from any additional surveys.
- At each time unit, predict the amount of removal effort necessary to achieve eradication. If more than one removal method is used, predict the most cost-effective mix of methods to achieve eradication based on costs per removal and the removal probability for each method.

The above tasks need to be updated progressively as the eradication program unfolds, and the results should be used to update the tasks undertaken during the next time unit of eradication activities. The models described above in section 3 can be used in an iterative fashion to update our estimates of the abundance and distribution of the pest population. The ability to combine monitoring information from multiple sources and to update analyses as new data are acquired will allow managers to determine if the residual population is becoming wary of particular removal methods, and hence implement alternatives. The "Eradication Progress" tool (**see section 6.1**) is a freely available and user-friendly online tool that implements some the models described above for assessing progress towards eradication.

4.2 Broadscale knockdowns

In some eradication operations, especially if the initial abundance of the target species is high, it may be more efficient to attempt a broadscale initial knockdown of the population (e.g. by poison baiting) before using other removal methods. In addition, for some pest species, broadscale poison baiting operations are the only removal technique that is feasible at large scales (e.g. invasive ants, brushtail possums). In these instances, a series of knockdowns are achieved using a predetermined number of broadscale aerial or ground-based baiting operations. In this situation progress towards eradication is usually only assessed following the completion of baiting operations using one of the monitoring protocols specified in section 2.2.

5 Proving Absence

5.1 Principles of proving absence from zero detections

It is almost impossible to provide statistical certainty about species absence, unless everywhere within the entire eradication extent is subject to surveillance using a detection method that is infallible. Hence, we usually assign degrees of confidence to species absence that provides a quantifiable level of uncertainty around a declaration of eradication success. For a species to be declared absent from an area with a given degree of confidence, surveillance must be undertaken to confirm (or otherwise) that the eradication has been successful (Samaniego-Herrera et al. 2013; Ramsey et al. 2009; Ramsey et al. 2011). This section presents the framework behind quantitatively proving eradication based on 'zero detection' data, as well as the process of planning a surveillance network to ensure that managers will have enough confidence in declaring eradication success.

Following the removal of the pest to the point where individuals are no longer being detected, a surveillance phase is then implemented, which involves looking for any individuals that may have survived the control phase. If there is evidence of the pest, it is obvious that the overall control operation has not been successful, and therefore eradication cannot be declared (assuming there are no false positive detections). However, if no individuals are detected, it does not necessarily mean absence of the target pest from the area, as individuals may have survived yet remained undetected.

Given no detections, our level of confidence in pest absence depends on:

1. How confident in eradication were we before doing surveillance? (i.e. how good was the control program)
2. How hard did we look for any pests that may have survived the eradication phase? (i.e. how good was the surveillance network)

We can use probabilities to quantify these confidence levels with Bayes' theorem as follows:

$$PoA = \frac{Prior}{1 - \left(SSe \times (1 - Prior)\right)} \tag{1}$$

The first factor in the list, termed the *Prior*, is the probability that eradication was successful before any surveillance was carried out. The term *SSe* is an abbreviation of system-level sensitivity: this is the probability of detecting the species if it was still present. It represents how good our detection/surveillance network is. Bayes theorem updates our prior knowledge (*Prior*) with data (*SSe*) to give the posterior probability of absence (*PoA*[1]).

Armed with Bayes' theorem, a *Prior* and the efficacy of our surveillance network (*SSe*; see Anderson et al. in review), we can calculate *PoA* and then make a management decision as to whether to declare eradication or not. If the calculated *PoA* it is not high enough, then we can carry out more surveillance (thus increase *SSe*) until we reach a value of *PoA* that we are comfortable with. An online user-friendly *PoA* tool is freely available for managers to guide the development of surveillance strategies or to analyse data to quantify confidence in eradication success, given no detections (**see section 6.2**).

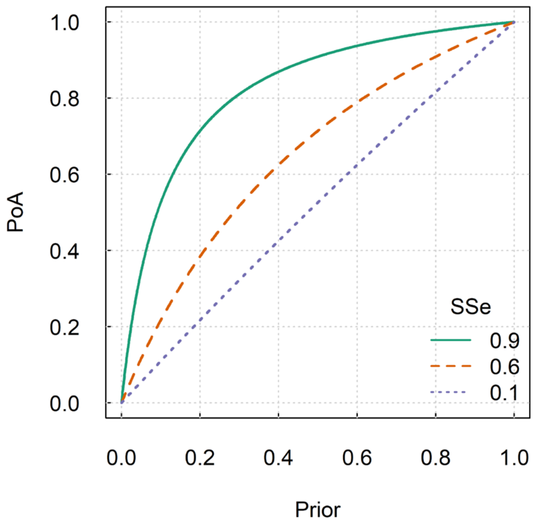

Figure 3. Contour plots showing the relationship between the prior (x-axis) and the resulting PoA (y-axis) for three levels of SSe (contour lines)

5.2 Specifying the Prior

As shown in Figure 3, the value specified for the *Prior* has a large influence on the level of surveillance that needs to be conducted in order to confidently declare absence of the pest. For example, if we have low confidence that control was sufficient to eradicate the pest (*Prior* = 0.5), then surveillance efforts need to be extremely high (yielding an SSe = 0.9) to achieve a high confidence in successful eradication (PoA > 90%). Conversely, if the *Prior* = 0.8, then surveillance efforts can be reduced (yielding an SSe = 0.6) to achieve the same level of confidence in absence of the pest (PoA > 90%).

[1] Reminder: this is as long as we do not detect anything during surveillance, because if we do then that means that eradication has not yet been successfully achieved.

As described above, specifying the prior is an important task, however there is no single method. Options include:

- In the absence of any information, it is recommended to specify a default prior from a BetaPERT distribution with a mean of 0.5, min = 0.1 and max = 0.9.
- Expert opinion/judgement: this can range from a single expert through to the collective prior distribution obtained from a number of experts using an elicitation approach (Ramsey et al 2009).
- Using information from similar previous attempts at eradication. For example, if a number of places have attempted a similar eradication and 60% of those have succeeded, then a mean prior could be set at 0.6.
- Derive a model-based prior using a computer model to simulate the planned control (see previous section) and use the proportion of runs where eradication was successful as a value for the prior (Nugent et al. 2018).
- A combined approach of the previous options – essentially an expert judgement, but it is informed by their knowledge of similar control operations, the modelled simulations and other factors (e.g. risk of reinvasions).

5.3 Setting the target for declaring success

The level of confidence in the probability of pest absence that is required (i.e. the target probability for deciding that eradication is successful and further surveillance efforts should stop) is essentially a management decision. It is impossible to achieve 100% certainty; therefore, a target stopping value must be chosen that is defensible and acceptable to stakeholders.

When setting a target, it may be beneficial to explicitly consider the costs associated with making a wrong decision (Gormley et al 2018). For example, if eradication is declared incorrectly (eradication is declared successful, but then the pest is detected at a later date), there may be substantial costs associated with having to repeat control and surveillance. In contrast, the costs of carrying out extensive surveillance may be excessive relative to mop-up re-control if the eradication fails. Socio-political factors should also be considered, such as what is the 'cost' associated with loss of public acceptance in the programme or loss of reputation if success is declared incorrectly? If this 'cost' is high, it may be might be better to set a higher stopping target value.

For example, in New Zealand, a target of 0.95 is typically used for declaring a management unit free of bovine tuberculosis. Therefore, control and surveillance must be carried out so that there is at least a 0.95 probability of TB freedom in wildlife. In theory this implies that one in twenty areas declared free will be incorrect declarations and will therefore require re-control at some point. However, this is seen as an acceptable level of risk when balanced against additional expensive surveillance activities required to achieve a higher stopping value (e.g *PoA* = 0.99).

5.4 Finding survivors: what is the worst-case scenario?

In the context of doing surveillance to confirm eradication success, the situation may arise in which managers think that they have achieved eradication before doing surveillance, but *n* survivors are subsequently detected. The question transitions from 'how confident are we that eradication has been achieved?' to 'what is the residual population abundance, given we have detected survivors?' Calculating the residual abundance is described above (**4.1 Estimating residual abundance**), which can be quite complex. However, there is a relatively simple way to use the *SSe* estimate from Proof of Absence modelling to estimate the upper limit of the residual population abundance (i.e. worst-case scenario). We can use the following equation to estimate the minimum abundance (*Y*) for which we can be 95% (or 99%) confident that the residual population abundance (*N*) is less than or equal given *n* detections $\left(P(N \leq Y|n)\right)$:

$$P(N \leq Y|n) = 1 - \prod_{P^*=n}^{Y}\left(1 - \binom{P^*}{n} SSe^{n}(1 - SSe)^{P^*-n}\right)$$

where the *SSe* is the system sensitivity calculated when attempting to detect a single survivor (i.e. minimum occupied cells = 1; Anderson et al. 2013). This does not provide an estimate of the population abundance, only a level of confidence that it is lower than a set number (*Y*). For example, consider a situation in which 2 individuals were detected during surveillance. When the *SSe* is 0.33, we can be 95% confident that the residual population abundance is ≤ 12 (Figure 4).

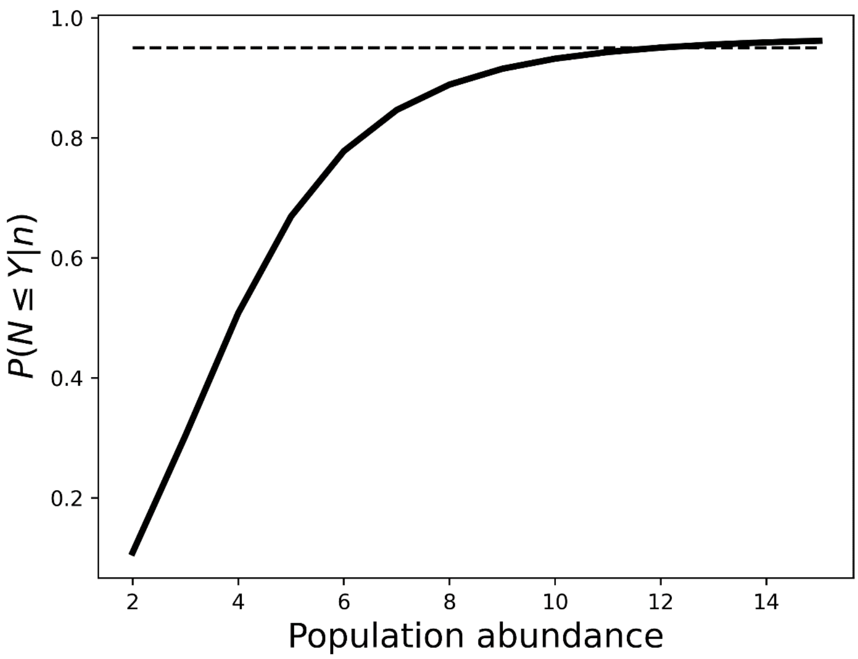

Figure 4. Probability that the residual population abundance (*N*) is less than or equal to *Y* $\left(P(N \leq Y|n)\right)$. In this example *SSe* = 0.33, number of detect animals (*n*) = 2, and target level of confidence = 0.95 (dashed horizontal line).

5.5 Planning surveillance

Surveillance is a costly and time-consuming endeavour. It is therefore in the interests of managers to carry out enough surveillance to achieve the target level of *PoA*, but no more. Similarly, insufficient surveillance risks allowing survivors in the pest population to reproduce into a large and renewed widespread problem. Quantitative planning increases the chances that a cost-effective surveillance strategy will be deployed.

We can rearrange equation 1 to determine the level of surveillance required (SSe_{Req}) to move our level of confidence in eradication from the *Prior* to the target *PoA*:

$$SSe_{Req} = \frac{PoA_{Target} - Prior}{PoA_{Target}(1 - Prior)} \tag{2}$$

For example, if *Prior* = 0.9 (i.e. we are 90% sure of eradication success after our control efforts) and PoA_{Target} = 0.95 (i.e. we want to be 95% sure of success), then SSe_{Req} = 0.53; this means that we need to do enough surveillance to have a 53% chance of detecting any remaining individual if there was one present (Figure 5). If, however, we wanted to be 99% sure of absence, then for the same prior, a much higher level of surveillance would be needed (i.e. SSe_{Req} = 0.91).

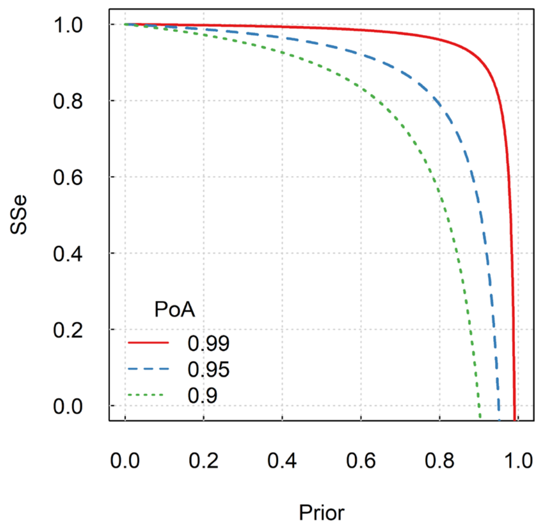

Figure 5. Contour plots showing the relationship between the *Prior* (x-axis), the *PoA* (contour lines) and the *SSe* (y-axis)

The important step for managers is converting SSe_{Req} to an actual surveillance network; that is, how many detection devices are needed and for how long do they need to be deployed? A good approximate estimate can be quickly calculated by first determining the area-wide sensitivity of a single device in the eradication area set for *n* nights, given by:

$$Se_n = 1 - \left(1 - \frac{2\pi g_0 \sigma^2}{Area}\right)^n$$

where g_0 is the nightly detection probability of an individual with a device at the centre of its home range, σ is the scale parameter of the home-range size (Ball et al. 2005) and *Area* is the size (m^2) of the area (i.e. management zone or full extent). The number of devices *D* required for *n* nights across the entire area can be calculated as:

$$D_n = \frac{ln(1 - SSe_{Req})}{ln(1 - Se_n)}$$

6 Decision Support Tools

As noted through this primer, we are developing several decision support tools that do the modelling discussed above as an aid to managers of eradication operations. This section contains a brief summary of those that are currently available:

6.1 Initial pre-eradication assessment tool

This web-based app is primarily to be used for undertaking an initial assessment of a pest population prior to undertaking eradication activities. The app is freely available at the following link https://landcare.shinyapps.io/assessment_app/. Below we provide some me guidance about the use of the app including the types of monitoring data as well as the associated models that can be used to undertake an initial assessment of a pest population.

The initial assessment app employs methods based on counts of individuals and presence of sign within sampling units. In general, monitoring data should be collected from sampling units that are independent. By independent, we mean that an individual counted (or recorded as present) on one sampling unit should not be able to be recorded on another sampling unit. This is different to the Proof of Absence (PoA) tool (**see section 6.3**) where sampling units are not required to be independent. Some particular models (e.g. `REST`) are tailored to particular types of sampling methods such as remote infrared cameras and require ancillary information to be collected. They also allow the relaxation of the strict assumption of independence of sampling units required by the other methods.

Models

The basic models in the initial assessment app can be divided into those that just require records of pest presence or absence from sampling units (i.e. `Occupancy` and `Royle-Nichols` models) and those that require counts of individuals to be recorded (i.e. `N-mixture` and `REST`). These are briefly described below:

Occupancy: This model implements the occupancy model of Mackenzie et al. (2006). It is primarily used to assess the area of the region occupied by the pest from presence/absence monitoring data. Occupancy estimates can also depend on habitat characteristics. Presence-absence data should be collected from sampling units that are independent.

Royle-Nichols: This model implements the occupancy model of Royle and Nichols (2003). However, this model has the occupancy rate being dependent on pest abundance and hence, can be used to provide an estimate of abundance in addition to occupancy. The extra parameter `K` can be provided here which is an upper limit on the likely abundance at each site. Larger values are preferred, but will increase the time to fit the model.

N-mixture: This model estimates pest abundance from counts of individuals collected from independent sampling units using the "N-mixture" model of Royle (2004). As for the "Royal-Nichols" model, the parameter `K` should also be provided.

REST: This model estimates pest density from encounters of individuals from camera traps using the "Random Encounter and Staying-Time" model of Nakashima et al (2018). In addition to recording the number of encounters at each camera, the "staying time" of each individual in front of the camera must also be recorded. The staying time can be estimated as the difference between the exit and entry times into the camera's field of view. This model also requires an estimate of the effective detection area of the camera (i.e. area within which detection of an individual is almost certain). This can be estimated using distance sampling techniques.

All models in the assessment app (and eradication progress app – section 6.2) require inputs in particular formats.

- Region boundary: An ESRI shapefiles that define the region of interest.
- Habitat raster: A single or multiple *.tif file(s) containing a map of habitat variable(s) that could be used predict spatially-varying abundance across the region.
- Detector locations: A csv file containing coordinates of monitoring devices in the same projection as the region boundary.
- Detection histories: A csv file containing a matrix of detection or counts with observations for each monitoring device in rows and repeat observations for each device (e.g. days) in columns.

In addition to the above, the REST model requires some additional data that is needed by that model.

- Stay: A csv file containing a single column with the residence time (i.e. seconds) that each encountered individual spent in front of the camera (i.e. the difference between exit and entry times).

- Censored: A csv file containing a single column containing a variable indicating whether the exit time for each encountered individual was observed (`censored` = 1) or unobserved (`censored` = 0).

- Active hours: The number of hours within a 24 hour period that the target species is usually active for. Species that are active at any time of the day would have a value of 24 and species active only at night would have a value around 12.

- Area of camera Viewshed: The area of the effective detection zone in front of a typical camera (m^2). This can be estimated using distance sampling techniques. An approximate area can be calculated by

$$A = \pi r^2 \times \frac{\theta}{360}$$

Where r is the maximum radial distance from a camera that a species would be detected with near certainty and θ is the coverage angle of the camera (in degrees). For more details on estimating an effective camera area, see Hofmeester et al. (2017).

- Viewshed area multiplier: The multiplier required to express density in units different from the units of the camera viewshed. If the camera viewshed is in m^2 then to express pest density in hectares the "viewshed multiplier" should be set to 10,000. If density in km2 is required, it should be set to 1,000,000.

6.2 Assessing eradication progress

This web-based app is primarily to be used for assessing progress towards eradication. As an eradication program progresses, and additional data become available, the app will provide updates on the estimate of the residual size of the pest population remaining or the residual proportion of occupied sites. The app is freely available at the following link https://landcare.shinyapps.io/eradication_app/. Below we provide some guidance about the use of the app including the types of monitoring data as well as the associated models that can be used to undertake progress toward eradication.

Consideration of the primary removal method is of great importance because the data collected from this method will be used to generate population estimates. For valid estimates to be obtained, the primary removal method must be able to remove individuals at a rate faster than they can be replaced. This can be easily visualised using a cumulative catch curve, which plots the cumulative catch (removals) of individuals against the catch per unit effort (CPUE) (Figure 6).

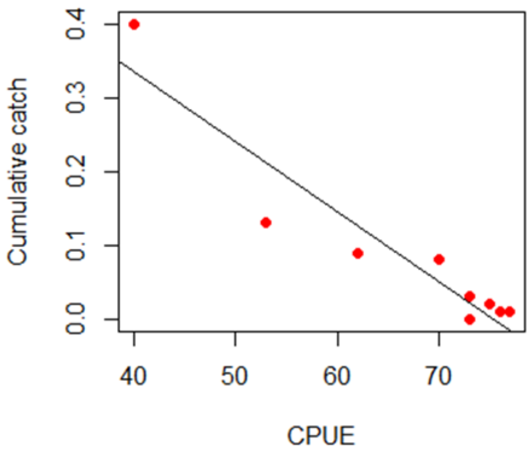

Figure 6. Plot of the relationship between CPUE and cumulative catch

The negative of the slope of this relationship is an estimate of the detection rate (also known as the catchability coefficient). If a clear negative relationship is not evident or there is evidence of a flattening of the relationship (non-linearity), then that suggests that the population might not be reducing at a rate high enough to achieve eradication or that the detection rate of individuals is declining. If this occurs, then alternative removal techniques need to be used. One problem with relying on the cumulative catch versus CPUE plot is that the relationship may suggest that all individuals have been removed, when in fact, eradication has not been achieved. This occurs because the relationship in Figure 6 assumes that detectability is constant for the duration of removal activities when in fact, the residual population is no longer susceptible to the removal method, (e.g. they may be trap-shy and therefore never get caught, resulting in detectability declining to zero). Identifying this situation depends on the use of a monitoring protocol running in parallel with the primary removal method that is able to detect residual survivors (e.g. cameras or scat-detecting dogs).

Models

The models in the eradication progress app are based on closed population removal estimators. This means that the models require data on the total catch of individuals of the pest species removed, at each sampling location, for each removal period (or "session"). Here a period refers to a distinct period of time where removal of the pest is actively occurring. For example, rodent trapping might be undertaken over four consecutive nights, once a month for five months. Hence, there are five periods or sessions with each period consisting of four nights trapping. Data from at least three periods are required for use in the models used here. These models also assume that the population is closed for the duration of the eradication program. In the example above this would mean that the rodent population is not subject to births, immigration, emigration or natural mortality over the five periods so the only change to the population is due to the removals. Alternative models that relax this assumption and allow for recruitment and natural losses to the population in addition to the removals will be added to the app soon. At the present the following models are available

- remGP: This model implements the catch-effort model of Gould & Pollock (1996). It is an aspatial model which means that removals are aggregated over all removal devices for each period. This means that device locations and habitat information are not used or required for this model. The catch and effort data are assembled from the removal histories by summing removals from each device, separately for each period. Effort data is calculated as the number of devices set in each period.

- remMN: This model implements the multinomial removal model of Haines (2018). Unlike remGP, device locations are required for this model and habitat information can be used to model spatial variation in initial abundance. Device locations are assumed to be independent.

- remGRM: This model estimates the generalised removal model of Dorazio et al. (2005). However, it also has the facility to include additional monitoring data into the analysis in addition to the removal data. The additional monitoring data are assumed to be derived from monitoring devices set in the same general vicinity (or a subset thereof) as the removal devices. Hence, the additional monitoring data should have the same number of rows and columns as the removal data and are uploaded into the app using `detection histories` button. Removal devices without an associated monitoring device should have an `NA` inserted for the appropriate row in `detection histories`.

All these models provide estimates of the initial abundance of the pest species (i.e. before the start of the eradication activities) as well as the residual abundance (abundance following eradication activities). As more eradication "sessions" are conducted, the updated detection history files should be uploaded into the app and revised estimates obtained. For more information about the use of this app, please consult the in-app help file.

6.3 TrapSim: Predicting removal rates with trapping

TrapSim (Gormley & Warburton 2017),[2] is an online tool that was adapted from the model of Glen et al (2017) with the intention of providing a simple user-interface to enable managers to run their own trapping simulations. It is a relatively simple tool with few parameters. It is web-based and therefore able to be accessed online and run by land-managers after minimal training or guidance. Having a simple model however comes at a cost in that a level of realism is sacrificed for the sake of simplicity and speed. A limitation of TrapSim is that it cannot model combinations of very large populations sizes nor very large trap networks due to the model structure of calculating the distance and probability of capture for every combination of trap and animal.

TrapSim is recommended for an exploratory first look at a trap network so managers can narrow down from among a wide range of options. It is a 'ready-reckoner' that allows for relative comparisons between proposed trap networks, allowing the manager to see whether they are in the right 'ball-park' in terms of a proposed trap regime. The simple user-interface and deployment on-line allows managers to run scenarios without requiring them to have knowledge of the underlying model, or training in quantitative ecology, coding, etc.

The model of Lustig et al (2019) can be used subsequently to further refine the trap network by including more levels of realism (e.g. immigration, higher flexibility in trapping regimes). The additional features mean that it is computationally more intensive than TrapSim, and therefore instead of running online, it is typically run on a high-powered computer. Furthermore, there is no user-interface and it is run via computer scripts. While this model can be made available to managers, it must be run by someone with expertise in the programming language. Lustig et al. (2019)'s model includes features

[2] TrapSim was written in the R programming language (R Core Team 2017), and implemented using the R packages shiny (Chang et al. 2016) and leaflet (Cheng and Xie 2016). It is freely available on the internet at **https://landcare.shinyapps.io/TrapSim**

such juvenile dispersal, immigration, and habitat specific density, and can be customised to model staggered roll-out of trapping across an area (e.g. Mahia reference).

6.4 Proof of Absence

The Proof of Absence (PoA) model is an online statistical tool for eradication managers to analyse surveillance data to quantify a posterior probability of absence of a target species given no detections have occurred. It has a user-friendly point-and-click interface to upload data and set parameter values. It is flexible to accommodate any species and any spatial scale (extent and sampling unit). The PoA Tool is freely available at https://landcare.shinyapps.io/shiny_poa/.

The modelling approach superimposes a grid-cell system on the area of interest (extent). The grid cells correspond to the sampling unit discussed above. The sampling unit for this model is set differently from that described in section 2.1 and should be much smaller than a typical home range of the pest species. Each sampling unit is characterized by a relative risk of where a pest could survive in the landscape and/or where an immigrant pest could settle after incursion in the area of interest. There are two general types of surveillance data that can be analysed by the model: point detection devices and grid-cell surveillance. Examples of point detection devices are traps, tracking tunnels, cameras and chewcards. Hunter or scent-dog GPS tracks can also be discretised to a set interval of points and be modelled as "point devices" (Anderson et al, in review). Each point device on the landscape has the potential to detect a pest that has a home-range centre in sampling units that surround the surveillance device. The detection parameters for point devices are g_0 and σ. An example of grid-cell surveillance is the probability that the public will detect a pest species in a given grid cell over the surveillance period. The associated parameters are the mean and standard deviation of the probability of detection over the surveillance period.

The PoA model relies on three different types of spatial data: 1) the boundaries of the area of interest; 2) the location of the surveillance devices, sentinel captures or grid surveillance; and 3) an optional grid of relative risk of pest survival or immigrant settling after control (Figure).

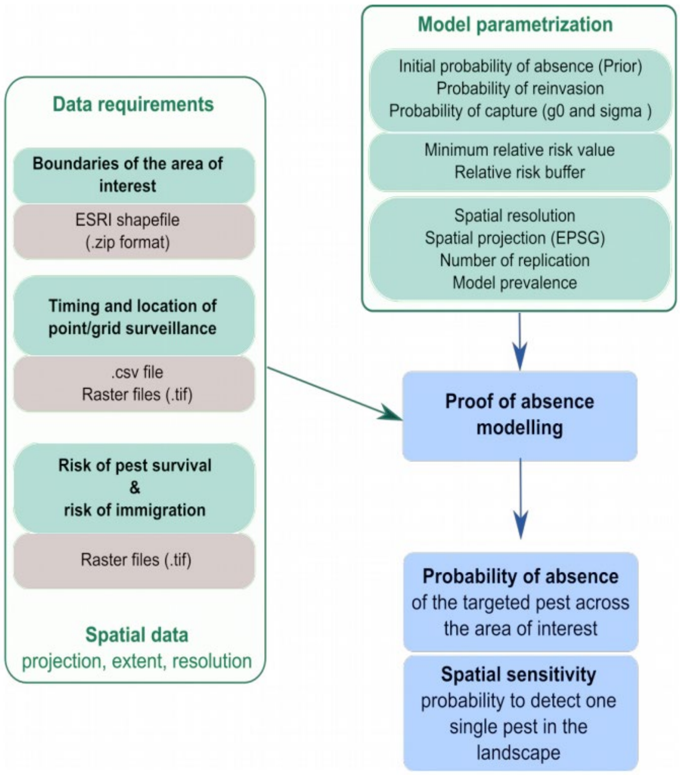

Figure 6. Diagram of Proof of Absence workflow, showing data requirements and input parameters. Results include predictions of the probability of absence, the overall system sensitivity, and a spatial map of surveillance sensitivity across the entire extent.

The user can partition the surveillance data into sessions (e.g. months or years) to assess how the probability of absence changes over time. In Figure 7 the target probability of absence is achieved in the middle of 2021, and the system sensitivity, or the probability of detecting at least one individual, increased annually.

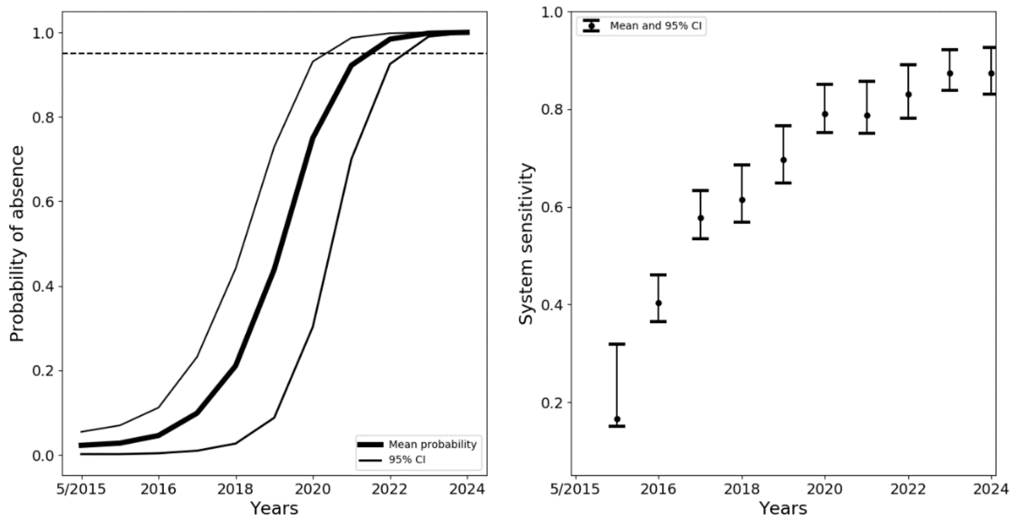

Figure 7. Graph of the *PoA* (left panel) of nutria in eastern United States (Anderson et al. in review). The *PoA* increases annually and exceeds the target probability of absence (dashed

horizontal line) in the middle of 2021. System sensitivity, or the probability of detecting at least one individual with the deployed surveillance (right panel).

6.5 Jess4Pests

JESS4Pests (Just Enough Surveillance Sensitivity For Pests) is an online tool that was developed for estimating how much surveillance is required to confidently prove absence of a pest. A screenshot of this web application can be seen in Figure 8; the tool is freely available at: https://landcare.shinyapps.io/JESS4Pests

Step1: The user enters the *Prior* and the Target value for *PoA* for their region and JESS4Pests calculates the required *SSe*. This value is then converted to the minimum number of total devices and devices per ha, based on:

- i the area targeted for eradication
- ii the detectability parameter (g_0)
- iii the home-range parameter (σ)
- iv the number of nights each device is set for.

Step 2: the user can explore various device spacings to achieve a layout that will match the number of devices that was calculated in Step 1. The tool will re-calculate the expected *SSe* that the user-specified detection array will yield and the subsequent *PoA* that would result. The user can also upload a planned detection network to see what level of *SSe* it will deliver.

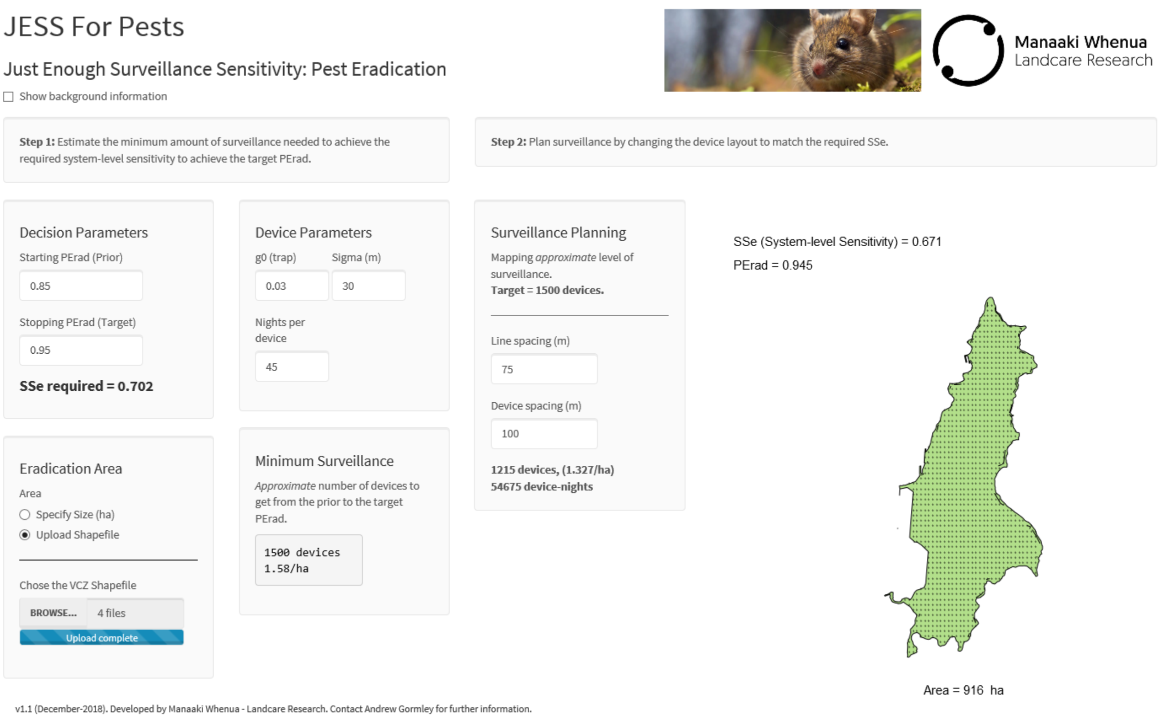

Figure 8: Screen shot of JESS4Pests with an example applied to Miramar Peninsula, Wellington

7 Summary/Synthesis

It is well established that invasive species are a threat to biodiversity, ecosystem function and services, and primary productivity (Gurevitch and Padilla 2004; Vitousek et al. 1997). Given the high financial expenditures required in perpetuity to minimize impacts through pest control (Pimentel et al 2001), eradication attempts are increasing in number and can result in important positive ecological outcomes (Cleeland et al. 2020; Jones et al. 2016; Russell and Holmes, 2015). However, eradication of an established species on any scale, large or small, is inherently difficult and financially expensive (Anderson et al. 2016, Cruz et al. 2009). Decisions associated with eradication operations need to be evidence based to ensure cost-efficient strategies are adopted and to satisfy concerns of funders, policy makers, managers and the public.

Policy and management decisions associated with the eradication process are divided into four phases : (1) assessing feasibility, (2) planning control strategies, (3) assessing progress (and revising strategies), and (4) assessing and confirming absence of the pest species. In this primer we have presented general methodologies and models for providing objective support for these decision processes. We covered a suite of easy-to-use and not-so-easy-to-use models that are available to eradication managers to obtain guidance for important decisions. The models can incorporate high levels of biological and operational complexity, but this comes at the cost of increased difficulty for users and may require the support of quantitative ecologists. Managers need to seek objective and quantitative support for their decisions. This may be through the use of available online tools, or consulting with quantitative ecologists. Answers to their questions can be found.

We have developed and made available important tools tailored for end-users that are freely available online and use a point-and-click graphical user interface. The initial assessment and eradication progress tools analyse a variety of data to inform on the initial extent of the pest population and progress towards eradication. A wider variety of data analysis methods (e.g. for search encounter data) will be added to these tools in the near future. The TrapSim tool is a simple simulation model that allows an exploration of the required effort to achieve eradication and the best strategy for deployment of pest control technologies (phases 1 and 2). The Proof of Absence tool is a statistical model that allows eradication managers to quantify a probability of absence of a target species given no detections have occurred (phase 4). This tool provides quantitative support to the decision to declare eradication success, estimates the additional amount of surveillance necessary to meet a target stopping point, or can be used to identify cost-efficient surveillance strategies. The Proof of Absence tool is flexible in that it can accommodate multiple surveillance methodologies and complex ecological attributes. In contrast, the Jess4Pests is a less flexible tool but easier to use. It can provide general guidance on surveillance effort required to meet objectives, such as the number of devices and spacing (phase 4).

The availability of all these online user-friendly tools, in addition to the more complex tools that require expert knowledge, create the potential to increase the cost-effectiveness of eradication operations. However, tools do not answer questions by themselves. Managers must plan to incorporate these tools early into the eradication program, which may require developing in-house quantitative capability or engaging external experts.

8 References

Anderson, D.; Ramsey, D.; Nugent, G.; Bosson, M.; Livingstone, P.; Martin, P.; Sergeant, E.; Gormley, A. & Warburton, B. (2013). A novel approach to assessing the probability of disease eradication from a wild-animal-reservoir host. *Epidemiology and Infection. 141*, 1509-1521.

Anderson, D.P.; McMurtrie, P.; Edge, K.-A.; Baxter, P. & Byrom, A. (2016). Inferential and forward projection modeling to evaluate options for controlling invasive mammals on islands. *Ecological Applications, 26*, 2548-2559.

Anderson, D.; Gormley, A.; Ramsey, D.; Baxter, P.; Nugent, G.; Martin, P.; Bosson, M.; Livingstone, P. & Byrom, A. (2017). A bio-economic decision process for in broadscale eradications of invasive pests and disease. *Biological Invasions, 19*, 2869–2884.

Anderson, D.P., Pepper, M.A., Travers, S., Michaels, T.A., Sullivan, K., Ramsey, D.S.L. (in review). Confirming the broadscale eradication success of nutria (*Myocastor coypus*) from the Delmarva Peninsula, USA. *Biological Invasions.*

Chen, C., Pollock, K. H., & Hoenig, J. M. (1998). Combining Change-in-Ratio , Index-Removal , and Removal Models for Estimating Population Size. *Biometrics*, *54*(3), 815–827.

Cleeland, J. B., Pardo, D., Raymond, B., Terauds, A., Alderman, R., Mcmahon, C. R., Phillips, R. A., Lea, M.-A. & Hindell, M. A. (2020). Introduced species and extreme weather as key drivers of reproductive output in three sympatric albatrosses. *Scientific Reports, 10, 8199.*

Cruz, F.; Carrion, V.; Campbell, K. J.; Lavoie, C. & Donlan, C. J. (2009). Bio-Economics of Large-Scale Eradication of Feral Goats from Santiago Island, Galápagos. *The Journal of Wildlife Management, [Wiley, Wildlife Society], 73*, 191-200.

Glen, A.; Latham, M.; Anderson, D.; Leckie, C.; Niemiec, R.; Pech, R. & Byrom, A. (2017). Landholder participation in regional-scale control of invasive predators: an adaptable landscape model. *Biological Invasions. 19*, 329-338.

Gormley, A. M. & Warburton, B. (2020). Refining kill-trap networks for the control of small mammalian predators in invaded ecosystems. *PLOS ONE, 15*, 1-12.Howe, E. J., Buckland, S. T., Després-Einspenner, M.-L., & Kühl, H. S. (2017). Distance sampling with camera traps. *Methods in Ecology and Evolution*, *8*, 1558–1565.

Gould, W. R., & Pollock, K. H. (1997). Catch-effort maximum likelihood estimation of important population parameters. Canadian Journal of Fisheries and Aquatic Sciences, 54, 890–897.

Gurevitch, J. & Padilla, D. K. (2004). Are invasive species a major cause of extinctions? *Trends in Ecology & Evolution, 19*, 470-474.

Holling CS (1978) Adaptive Environmental Assessment and Management. John Wiley and Sons, London

Jones, H. P., Holmes, N. D., Butchart, S. H. M., Tershy, B. R., Kappes, P. J., Corkery, I., Aguirre-Muñoz, A., Armstrong, D. P., Bonnaud, E., Burbidge, A. A., Campbell, K., Courchamp, F., Cowan, P. E., Cuthbert, R. J., Ebbert, S., Genovesi, P., Howald, G. R., Keitt, B. S., Kress, S. W., Miskelly, C. M., Oppel, S., Poncet, S., Rauzon, M. J., Rocamora, G., Russell, J. C., Samaniego-Herrera, A., Seddon, P. J., Spatz, D. R., Towns, D. R. & Croll, D. A. (2016). *Invasive mammal eradication on islands results in substantial conservation gains. Proceedings of the National Academy of Sciences, 113, 4033-4038.*

Lustig, A.; James, A.; Anderson, D. & Plank, M. (2019). Pest control at a regional scale: Identifying key criteria using a spatially explicit, agent-based model. *Journal of Applied Ecology. 56*, 1515-1527.

MacKenzie, D. I., Nichols, J. D., Royle, J. A., Pollock, K. H., Bailey, L. L., & Hines, J. E. (2006). *Occupancy estimation and modelling: inferring patterns and dynamics of species occurrence*. Academic Press.

Martin, A. R. & Richardson, M. G. (2019). Rodent eradication scaled up: clearing rats and mice from South Georgia. *Oryx. 53*, 27–35

Moeller, A. K., Lukacs, P. M., & Horne, J. S. (2018). Three novel methods to estimate abundance of unmarked animals using remote cameras. *Ecosphere*, *9*(8), e02331.

Murphy, E. C.; Russell, J. C.; Broome, K. G.; Ryan, G. J. & Dowding, J. E. (2019). Conserving New Zealand's native fauna: a review of tools being developed for the Predator Free 2050 programme. *Journal of Ornithology, 160*, 883-892.

Nakashima, Y., Fukasawa, K., & Samejima, H. (2018). Estimating animal density without individual recognition using information derivable exclusively from camera traps. *Journal of Applied Ecology*, *55*(2), 735–744. https://doi.org/10.1111/1365-2664.13059.

Nugent, G.; Gormley, A. M.; Anderson, D. P. & Crews, K. (2018). Roll-Back Eradication of Bovine Tuberculosis (TB) From Wildlife in New Zealand: Concepts, Evolving Approaches, and Progress *Frontiers in veterinary science. 5*, 277-277.

Pimentel, D., McNair, S., Janecka, J., Wightman, J., Simmonds, C., O'Connell, C., Wong, E., Russel, L., Zern, J., Aquino, T. & Tsomondo, T. (2001). Economic and environmental threats of alien plant, animal, and microbe invasions. *Agriculture, Ecosystems & Environment, 84*, 1-20.

Ramsey, D. S. L.; Efford, M. G.; Ball, S. & Nugent, G. (2005). The evaluation of indices of animal abundance using spatial simulation of animal trapping. *Wildlife Research, 32*, 229-237.

Ramsey, D. S. L.; Parkes, J. & Morrison, S. A. (2009). Quantifying Eradication Success: the Removal of Feral Pigs from Santa Cruz Island, California. *Conservation Biology, 23*, 449-459.

Ramsey, D. & Efford, M. (2010). Management of bovine tuberculosis in brushtail possums in New Zealand: predictions from a spatially explicit, individual-based model. *Journal of Applied Ecology, 47, 911-919.*

Ramsey, D.; Parkes, J.; Will, D.; Hanson, C. & Campbell, K. (2011). *Quantifying the success of feral cat eradication, San Nicolas Island, California. New Zealand Journal of Ecology, 35, 163-173.*

Robinson, S. A. & Copson, G. R. (2014). *Eradication of cats (Felis catus) from subantarctic Macquarie Island. Ecological Management & Restoration, 15, 34-40.*Royle, J.A. (2004). Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation*, *27*(1), 375–386.

Royle, J Andrew, & Nichols, J. D. (2003). Estimating abundance from repeated presence–absence data or point counts. *Ecology*, *84*(3), 777–790.

Russell, J. C.; Binnie, H. R.; Oh, J.; Anderson, D. P. & Samaniego-Herrera, A. (2016). Optimizing confirmation of invasive species eradication with rapid eradication assessment. *Journal of Applied Ecology, 54*, 160-169.

Russell, J. C. & Holmes, N. D. (2015). Tropical island conservation: Rat eradication for species recovery. *Biological Conservation, 185*, 1 – 7.

Samaniego-Herrera, A.; Anderson, D.; Parkes, J. & Aguirre-Muñoz, A. (2013). Rapid assessment of rat eradication after aerial baiting. *Journal of Applied Ecology, 50*, 1415-1421.

Thomas, L., Buckland, S. T., Rexstad, E. A., Laake, J. L., Strindberg, S., Hedley, S. L., Bishop, J. R. B., Marques, T. A., & Burnham, K. P. (2010). Distance software: Design and analysis of distance sampling surveys for estimating population size. *Journal of Applied Ecology*, *47*(1), 5–14. https://doi.org/10.1111/j.1365-2664.2009.01737.x

Thompson, W. L., White, G. C., & Gowan, C. (1998). *Monitoring Vertebrate Populations* (1st ed.). Academic Press.

Vitousek, P. M., D'Antonio, C. M., Loope, L., Rejmanek, M. & Westbrooks, R. (1997). Introduced species: a significant component of human-caused global change. *New Zealand Journal of Ecology, 21*, 1-16.

Walters CJ (1986) *Adaptive Management of Renewable Resources*. MacMillan Publishing Company, New York, New York, USA

CENTRE FOR
INVASIVE SPECIES SOLUTIONS

WWW.INVASIVES.COM.AU