



CENTRE FOR  
INVASIVE SPECIES SOLUTIONS

# TOOLS FOR DEVELOPING COST-EFFECTIVE DECISIONS FOR MANAGING INVASIVE PEST ERADICATIONS

FINAL REPORT FOR PROJECT P01-I-005

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# **TOOLS FOR DEVELOPING COST-EFFECTIVE DECISIONS FOR MANAGING INVASIVE PEST ERADICATIONS**

## **FINAL PROJECT REPORT FOR PO1-I-005**

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# INTRODUCTION

Incursions of invasive animal and plant pests pose severe threats to ecosystems, threatening biodiversity and causing losses to agricultural productivity (Myers et al. 2000; Simberloff 2009). Early intervention that eradicates new pests before they become established offers some of the highest benefit-cost ratios in biosecurity policy (Baxter et al. 2008). Once a decision is made to initiate eradication of a pest, managers are then faced with decisions about how and when to proceed (Wenger et al. 2018). At the other end of the scale, once eradication appears to be successful and the pest is no longer detected, a decision must be made about whether to stop the eradication program and declare success (Morrison et al. 2007; Ramsey et al. 2009). In practice, these decisions about how to manage an eradication response are usually based on subjective reasoning rather than scientific evidence (Russell and Blackburn 2017).

Eradicating a pest species from an area requires removing all individuals and simultaneously preventing reinvasion (Bomford and O'Brien 1995). The list of international eradications is growing rapidly for diverse taxa, with 1,550 eradication events recorded in the Database of Island Invasive Species Eradications (Spatz et al. 2022). New technologies and evidence-based strategies (Nugent et al. 2018; Murphy et al. 2019) are allowing for increasingly larger islands and mainland areas to be eradicated (Cruz et al. 2005; Carrion et al. 2011; Anderson et al. 2022). With eradication programs becoming increasingly more ambitious and logistically difficult, provision of evidenced-based criteria for evaluating the progress and success of eradication programs is becoming more critical.

This project aimed to develop an evidence-based approach for managing invasive pest eradications by developing tools to help managers make more cost-effective decisions during an eradication response. These tools were developed to follow a logical framework for conducting pest eradications and to provide near real-time analysis of data that can be used to support the decision-making process. The overall objective of the decision-support tools is to allow managers to make near-optimal (cost-effective) decisions when deploying resources.

The decision tools developed as part of this project were packaged in a user-friendly software interface that could be applied generally to any invasive pest-eradication response. Management decisions associated with the eradication process were divided into three phases: (a) assessing feasibility and planning control strategies, (b) assessing progress (and revising strategies), and (c) assessing and confirming absence of the pest species. More specifically, the decision tools were designed to address the following set of decisions:

- a) What is the feasibility of eradication (likelihood that the response will fail)?
- b) What are the most cost-effective removal and surveillance strategies (which tools)?
- c) How do we measure progress towards eradication (what future resources are required for completion)?
- d) When can we declare success?

This report outlines the development of these decision tools and illustrates their functionality and use for supporting decision-making during pest-eradication programs.

# METHODS

## USING ERADICATION CASE STUDIES TO DEVELOP A RESPONSE FRAMEWORK SHOWING DECISION PATHWAYS

To provide context and needs requirements to guide the development of the decision-support tools, managers of current pest-eradication programs were engaged to determine the types of operational data that are routinely collected during an eradication response. The case studies were analysed to determine:

- the types of decisions managers face during an eradication response
- the types of data routinely collected during an eradication response that could be used in the decision-making process
- the types of constraints that may affect the decision-making process.

To this end, managers were engaged from several current eradication programs (Table 1). This included providing advice and assisting with data analysis as well as soliciting information needs required in the decision-making process during an eradication response.

Table 1. Current pest-eradication programs that were engaged in developing the eradication decision-support tools project

Eradication program	Agency	Location
<b>Coati (<i>Nasua narica</i>)</b>	Island Conservation	Robinson Crusoe Island, Chile
<b>Red fire ants (<i>Solenopsis geminata</i>)</b>	Queensland Department of Agriculture and Fisheries	Brisbane, Queensland
<b>Electric ants (<i>Wasmannia auropunctata</i>)</b>	Queensland Department of Agriculture and Fisheries	Cairns, North Queensland
<b>Feral cats (<i>Felis catus</i>)</b>	Port Phillip CMA	French Island, Victoria
<b>Nutria (<i>Myocastor coypus</i>)</b>	USDA, Maryland	Delmarva Peninsula, USA
<b>Brushtail possum (<i>Trichosurus vulpecula</i>)</b>	Hawkes Bay Regional Council	Mahia Peninsula, NZ
<b>Feral goats (<i>Capra hircus</i>)</b>	Taranaki Regional Council	Mount Taranaki

As a result of feedback from managers of current eradication programs, a general eradication response framework was developed. This framework outlined the general pathway of the decisions required during a general eradication response. This framework (outlined below) was then used to develop the functionality of the decision-support tools, which were designed to support the decision-making process.

## THE THREE PHASES OF AN ERADICATION RESPONSE: ASSESS, ERADICATE, EVALUATE

A structured framework was developed for guiding decisions around the response to eradicate invasive pests (Figure 1). This framework consists of several phases, broadly categorised into assessment, eradication and evaluation phases. Each phase represents a discrete stage in the management of an incursion/eradication response and has its own set of questions, activities or knowledge requirements. The framework is generic, in that it could be applied to the management of an eradication program applied to any specific taxa and broadly sets out the logical flow of activities. In brief, these are as follows.



*Assessment phase:* In this phase, the feasibility of eradication is assessed. Managers directing an eradication response firstly gather information on relevant aspects of the species biology, approximate abundance and spatial distribution of the pest prior to the commencement of eradication activities. These can be derived from preliminary monitoring data or expert opinion. Information on the likely methods and/or tools to be used to conduct the pest eradication are also assembled and used to design an eradication strategy, which may be governed by an overall budget. Various eradication strategies can then be examined to determine whether eradication is feasible. Eradication feasibility can be assessed on purely technical terms, based on the properties of the proposed pest-removal methods, or on bioeconomic terms, to determine whether eradication can be achieved for a fixed budget. If eradication is not technically feasible or cannot be achieved for a set budget, then focus shifts to the design of an exit strategy, which may involve containment and/or asset protection.

*Eradication phase:* In this phase, data collected during on-ground eradication activities, including monitoring and surveillance, is used to infer population trajectories and associated detection rates for each method employed. Progress towards eradication is assessed for a series of control 'sessions', a period where intensive pest-removal activities and/or monitoring occurs over the entire extent of the area of interest or a section thereof. Small eradication programs may only consist of a single session over the entire extent, but more complex programs may consist of many such sessions occurring within many discrete sections covering the area of interest (i.e. management units). Data collected during on-ground activities consists mainly of the number of individual pests removed and the associated control effort deployed. Otherwise, monitoring of pest abundance or sign is undertaken (e.g. when poison baiting is for control). Initial analysis focuses on examining pest-removal rates to determine whether they are sufficient to cause population decline and, if so, provide estimates of residual population abundance for each session of the eradication program. These estimates can then flow back into the assessment phase, allowing examination of the optimal mix of further removal activities that should lead to nominal eradication (i.e. zero detections).

*Evaluation phase:* This phase is mainly concerned with a quantitative assessment of proof of absence, that is, when pests are no longer being detected and eradication is suspected to have occurred. Structured and unstructured surveillance data are combined with decision theory to find the optimal amount of surveillance, where no pests are detected, to declare eradication successful using stopping rules based on an agreed threshold for the probability of eradication. If pests are detected during evaluation phase monitoring, then eradication is unsuccessful and the program shifts back into the eradication phase for further pest control or mop-up operations. If evaluation surveillance does not detect any pests, eradication is declared at the associated probability and confidence levels. Surveillance may still continue, however, in the form of low-cost passive surveillance, which provides added assurance of eradication success and can also be useful for detecting re-invasion. This becomes especially important when the area of interest has multiple management units that are each treated in sequence.

Before introducing the functions of the decision-support tools that were developed to support activities in the phases of an eradication response, the report begins with some initial considerations about the area of interest (extent) of the pest species and how it should be partitioned for operational activities.

## **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 2). The 'extent' is the entire area over which the program 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. The size of sampling units needs to be tailored to the biology of the pest species. Ideally, sampling units should be large enough to encompass an average home-range size for animal pests. Hence, sampling units should be large enough such that there is limited movement of individuals between sampling units.

For relatively small-area eradications, such as rodent eradications from small offshore islands with aerial toxin drops (e.g. Samaniego-Herrera et al. 2013), the entire extent can be controlled and surveyed quickly. In this case, a single (notional) management zone can cover the entire extent. When the eradication extent covers a very large area, and it cannot be entirely controlled or surveyed relatively quickly, then the extent should be subdivided into management zones and a two-stage broadscale eradication approach 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 absence in the zone. The management zone is passed into Stage II when a high confidence in absence is achieved, which allows reallocation of resources to other management zones. For clarity, the term ‘freedom’ refers to the complete removal of pests from a management zone, 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 (Figure 2). 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).

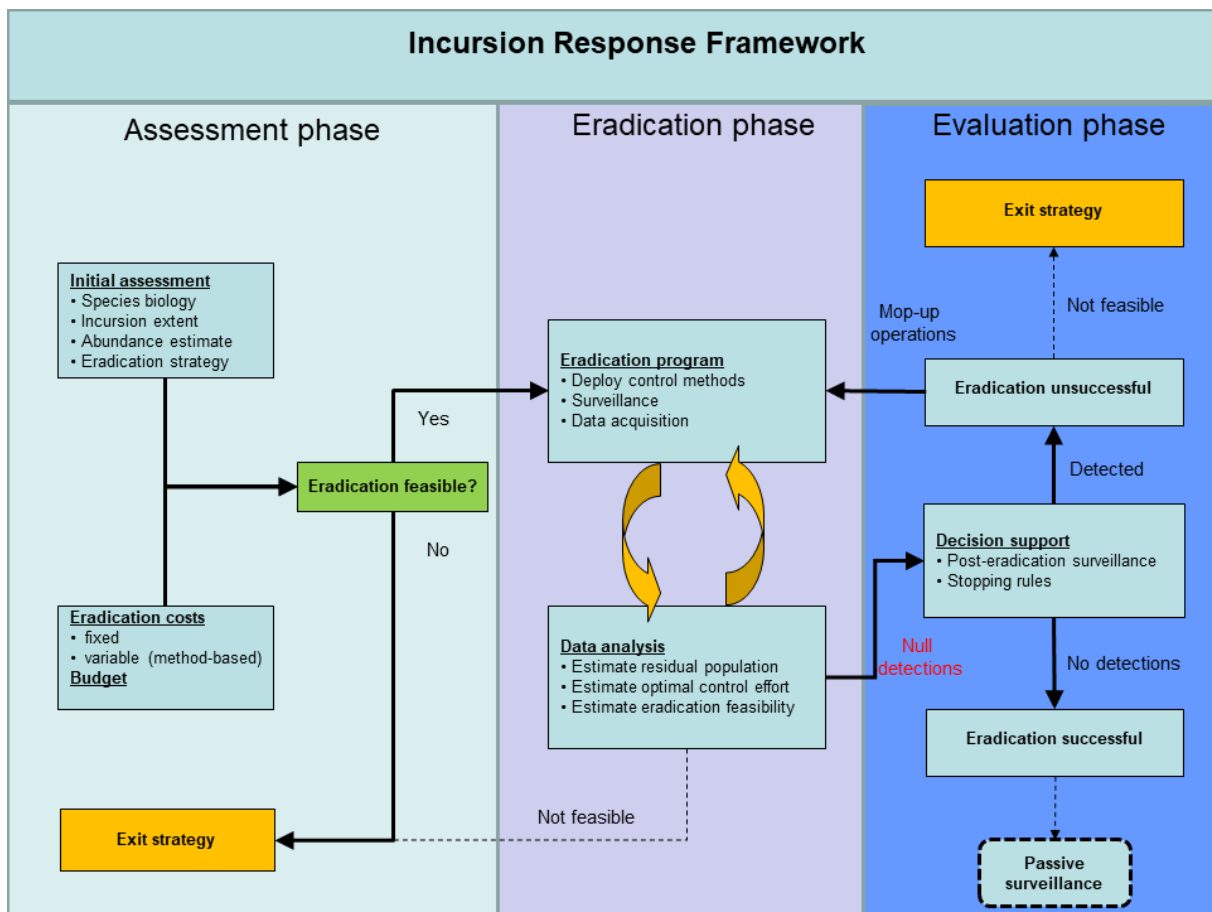


Figure 1. The eradication response framework. Each phase partitions distinct activities undertaken during an eradication response that are associated with a purpose-designed decision-support tool.



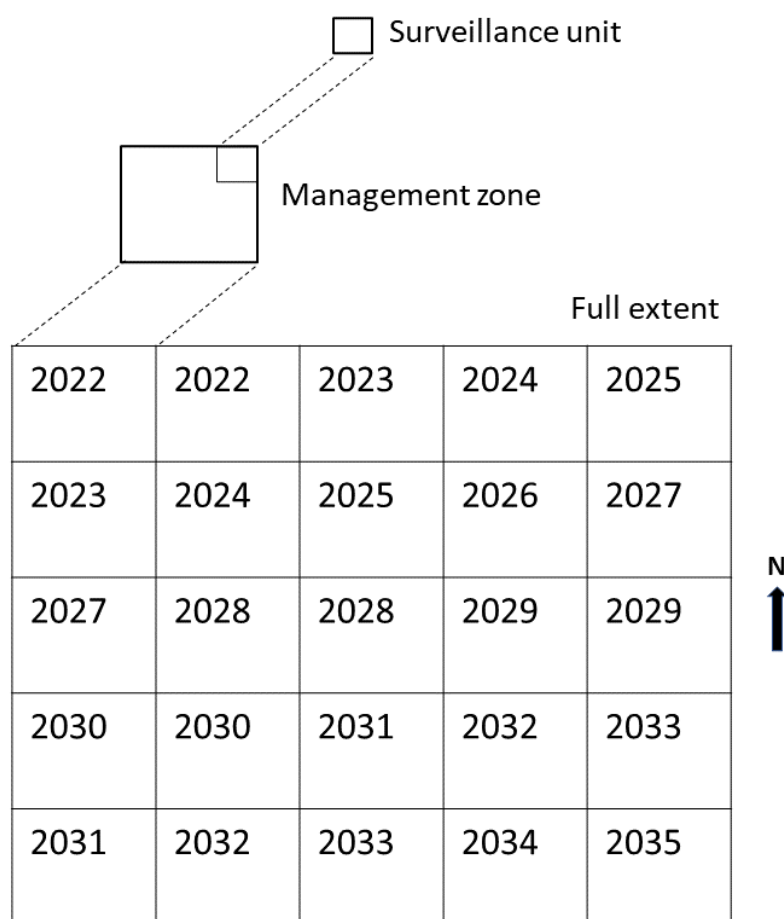


Figure 2. The spatial structure of a hypothetical broadscale eradication operation (Anderson et al. 2017). The smallest square is the sampling unit, which is nested in a management zone, which is nested in the full extent (broadscale area). The conceptual eradication begins in the north-west of the region in 2016 and finishes in the south-east in 2035.

## ASSESSMENT PHASE

### ASSESSING ERADICATION FEASIBILITY

To successfully achieve eradication, three essential criteria must be met: (a) the rate of removal exceeds the rate of increase of the pest, (b) immigration is prevented, (c) all potentially reproductive individuals are put at risk (Bomford and O'Brien 1995). Three additional desirable criteria for determining whether eradication is preferred to sustained control are: (d) individuals can be detected at low densities, (e) cost-benefit analysis favours eradication over sustained control, and (f) there is sociopolitical support for eradication.

If it is reasonable to assume that criteria b–f above can be met, 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 and extent of the pest. Given this knowledge, how can the best control strategy be chosen to achieve eradication? A wide range of control tools are available, the choice of which depends on factors such as the habitat where the target species occurs. For some species, aerial deployment of toxic bait may be the preferred and sometime only viable method of pest control. For other species, pest control may be undertaken using bait stations, trapping, hunting (aerial or ground) or some combination of these.

Even for a single control method, many decisions need to be made. For example, if trapping is to be used, the manager 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 traps will be deployed).

One way of selecting an appropriate control regime is to use a computer model that simulates pest removal. This enables a quick comparison of the relative effects on pest abundance across a wide range of control options. 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 removal of individuals from a pest population (Anderson et al. 2016; Glen et al. 2017; Lustig et al. 2019). The general approach assumes that removal devices, such as traps or bait stations, are represented by georeferenced point locations within the area of interest. 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 and density that is placed randomly in the landscape with locations corresponding to the home-range centres of individuals. Alternatively, the distribution of home-range centres could depend on habitat preferences. 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  $\sigma$  (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  $2.45\sigma$ , which defines the area where an individual spends 95% of its time. Note that values of the  $g_0$  and  $\sigma$  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  $\rho$  is the device density (per m<sup>2</sup>). 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  $\theta$  is the removal rate per unit of search effort,  $k$  is the number of days and  $\rho$  is the total amount of search effort, per day, within the unit. Typically,  $\theta$  can be estimated from samples of removal and effort data, collected from at least three sampling periods (Gould and Pollock 1997).

Other components of population dynamics are included in the simulation models. The number of new offspring born each reproductive period is simulated as draws from a Poisson distribution with mean  $\lambda$ , 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.

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

## ERADICATION FEASIBILITY DECISION-SUPPORT TOOL

A web-based Eradication Feasibility decision-support tool (Figure 3) was developed using the Shiny web application development package (Chang et al. 2022) within the R language (R Development Core Team 2020). The app is available at <https://landcare.shinyapps.io/Eradsim/>.

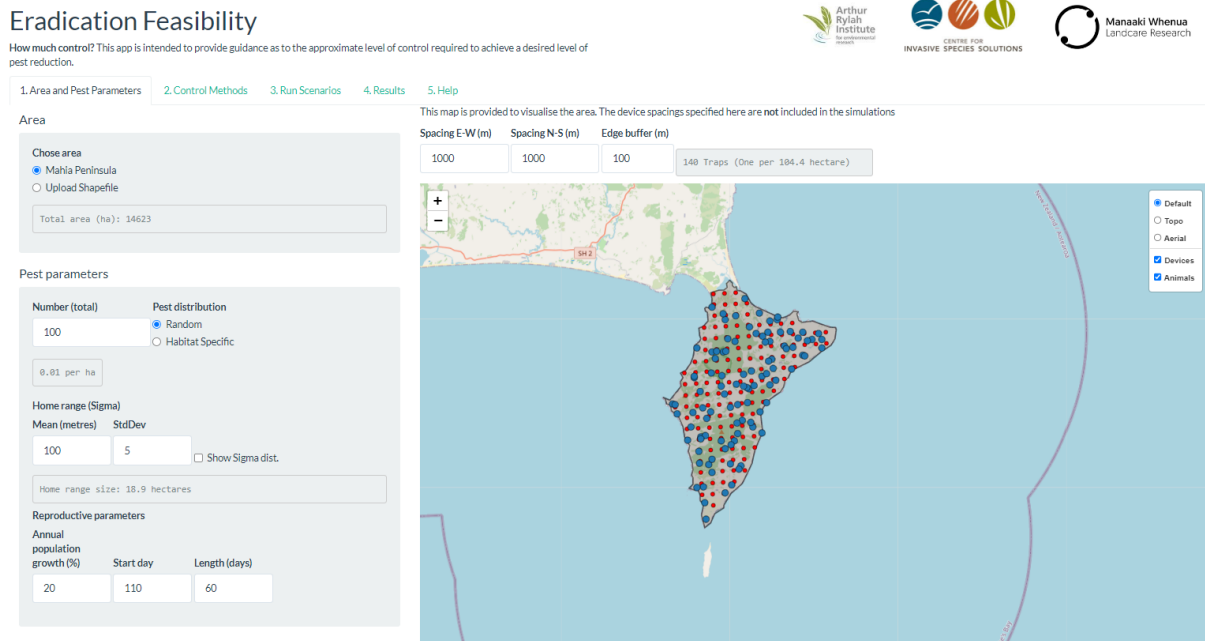


Figure 3: Screenshot of the Eradication Feasibility decision-support tool

The app allows the user to simulate various combinations of pest control methods in order to determine which is most likely achieve the desired level of reduction for the minimum cost. The user must first read in a shapefile of the regional boundary of their area (in Esri shapefile format) in a projected coordinate system with units in metres. If available, a raster of relative abundance for the pest (i.e. by habitat) can be supplied (either as an .asc or .tif file). In the absence of this information, individuals are allocated randomly across the landscape. The user must also provide species-specific information, including home-range size and annual population growth.

Currently, four control methods can be simulated: (a) trapping, (b) bait stations, (c) hunting, and (d) aerial poisoning. The user constructs each control scenario by specifying the control method(s); either a single or multiple concurrent methods can be specified. Each control method has a number of parameters that must be specified.

For trapping, the user provides the trap spacings in the E–W and N–S directions, the trappability ( $g_0$ ), the maximum trap capacity, the start day, duration of trapping, the interval between trap checks, as well as information related to costs including the number of traps able to checked per day, the day rate (\$) for a field technician and the fixed cost (\$) per trap (Figure 4). Bait-station information is similar to trapping in that stations are specified in the E–W and N–S directions, bait-station kill probability ( $g_0$ ), start night, duration and checking interval (Figure 4).

Trapping

Trapping Method 1

Spacing E-W (m)	Spacing N-S (m)	Daily bycatch	Max catch	Trap Probability (g0) Mean	StdDev	Proportion untrappable	Start night	Duration (nights)	Check interval	Traps checked per day	Day rate (\$)	Fixed cost per trap (\$)
500	500	0.01	1	0.1	0.01	0.05	5	30	7	40	400	25

563 Traps  
Cost = \$48875

☐ Second Trap Method

Bait Stations

Spacing E-W (m)	Spacing N-S (m)	Daily rate of failure	Bait Station Probability (g0) Mean	StdDev	Proportion unbaitable	Start night	Duration (nights)	Check interval	Bait stations checked per day	Day rate (\$)	Bait costs (\$/station/day)	Fixed cost per bait station (\$)
500	500	0	0.1	0.01	0.05	35	50	25	40	400	5	60

563 Bait Stations  
Cost = \$59625

Figure 4: Screenshot of parameter inputs for trapping and bait stations

Hunting is specified in terms of the distance per day (km) covered by a hunter and the kill rate (i.e. removal rate). A raster can optionally be specified that delimits the areas being hunted (Figure 5). These parameters are combined to give the daily probability of an individual animal being killed. The value of the distance per day and kill rate can be changed to simulate ground or aerial hunting. Aerial poisoning is specified as a per cent kill for the area that is being treated, which, like hunting, can be delimited by a raster file (Figure 5).

Hunting

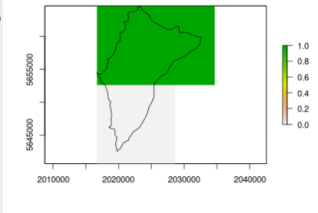
Hunting Method 1

Start day	Days hunted	Distance per day (km)	Kill rate	Day rate (\$)
30	10	5	0.5	2500

Cost = \$25000 ☒ Hunting mask

Chose the hunting mask

Browse... hunt\_mask\_ Upload composite



☐ Effort vs prob of kill

Aerial poison

Start day	Operation length	Percent kill	Cost per hectare (\$)
60	5	90	20

Cost = \$144058 ☒ Aerial mask

Chose the aerial mask

Browse... pois\_mask\_ Upload composite

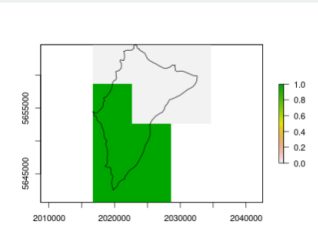


Figure 5: Screenshot of parameter inputs for hunting and aerial poisoning

When the user-defined control scenarios have been specified, the user can then simulate them. The main outputs from the decision tool include the mean population size remaining and the total cost of control, as well as information such as the number of kills by each method and the population size over time (Figure 6). The user can quickly see which (if any) of the scenarios resulted in the required control efficacy and the cost of each.

The Eradication Feasibility decision-support tool is not intended to provide accurate predictions of residual population size, but rather to show the relative efficacy of each scenario.

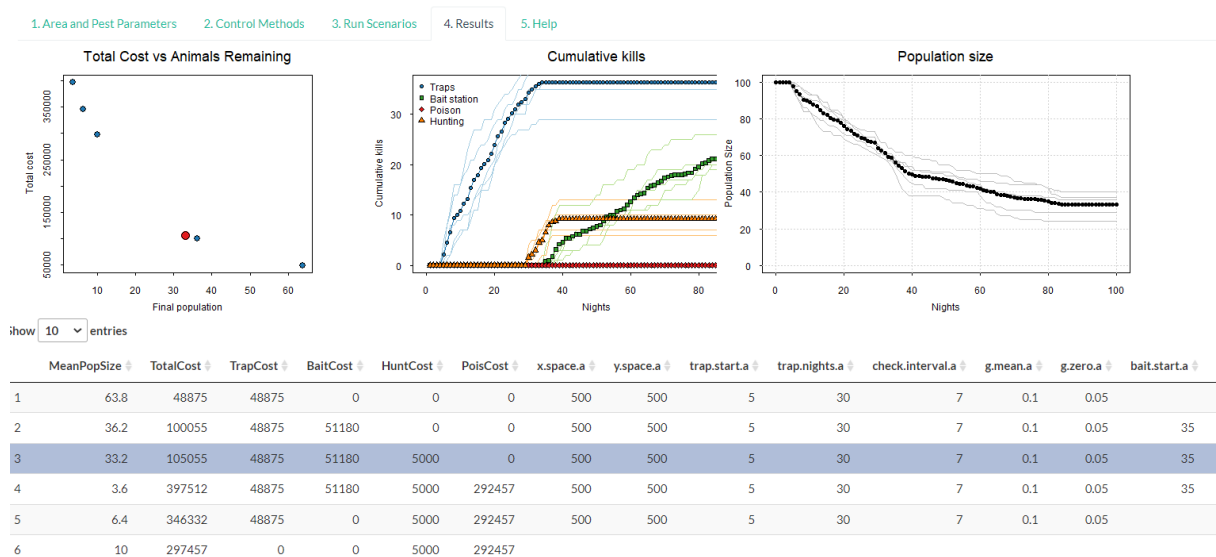


Figure 6: Simulated outputs from six control scenarios. For example, the highlighted scenario (3) consisted of a combination of trapping, baiting and hunting and resulted in  $n = 33$  animals remaining at a cost of \$105,055.

## ERADICATION PHASE

### ASSESSING ERADICATION PROGRESS

During eradication activities, when active pest removal is occurring, data on the number of pests removed and effort expended should be routinely collected (but see below). These operational data can be used to assess the removal rate of pests and provide an estimate of population abundance. Note that this assessment uses the operational data and does not require any additional monitoring data to be collected, although this can be incorporated if available. Once sufficient removal and monitoring data have been collected, analyses of these data can then be used to provide periodic updates of the residual population size. These estimates can then be fed back into the Eradication Feasibility decision-support tool to predict the amount of additional effort required to achieve eradication. In the latter case, if removal costs are known, the further cost required to achieve nominal eradication can be predicted.

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, house mice). 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 cannot be assessed with operational data and must therefore be assessed by systematic monitoring of the pest population. A separate decision-support tool has been developed that enables estimation of residual population size from unmarked abundance monitoring data (e.g. camera traps) or pest species occupancy from presence-absence data (e.g. sign surveys).

The tasks undertaken to assess progress towards eradication will therefore involve:

- analysing operational and monitoring data collected during control activities
- checking for adequate rate of pest removal
- estimating residual population abundance or the proportion of occupied sites.

Use the above estimates to 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 session of eradication activities. The

decision-support tool described below (Eradication Progress decision-support tool) can be used iteratively to update 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 declining or becoming wary of particular removal methods.

## ERADICATION PROGRESS DECISION-SUPPORT TOOL

The web-based Eradication Progress decision-support tool (Figure 7) was developed using the Shiny web application development package (Chang et al. 2022) within the R language (R Development Core Team 2020). The app is available at [https://landcare.shinyapps.io/eradication\\_app/](https://landcare.shinyapps.io/eradication_app/). Some guidance about using the tool is provided below, including the types of monitoring data as well as the associated models that can be used to assess progress towards eradication. All the models and functions underpinning the Eradication Progress decision-support tool are available in a purpose-built R package 'eradicate', developed as part of this project and available at <https://github.com/eradicate-dev/eradicate>.

The models and analyses in the Eradication Progress decision-support tool are based primarily on removal data. This means that the models require data on the total number of individuals of the pest species removed, at each sampling location, for each removal session. Here a session refers to a distinct phase of time where removal of the pest is actively occurring. For example, rodent trapping might be undertaken over 20 consecutive nights and then repeated six months later. Hence, there are two sessions, separated by 6 months, with each session consisting of 20 nights trapping (i.e. 20 periods per session). The distinction between 'sessions' and 'periods' within sessions is important, as it underlies the data format required by the models used here (Figure 8). Populations are assumed to be closed within a session. That means, within a session, the population is not subject to births, (natural) deaths, immigration or emigration, and the only change to the population is caused by the removal process over each period. However, between sessions, populations can be assumed to be subject to these natural additions and/or losses (Figure 8). The eradication progress decision-support tool contains models that cater for both these scenarios. Data from a minimum of three periods of control per session are usually required to generate an estimate of population abundance using removal data.

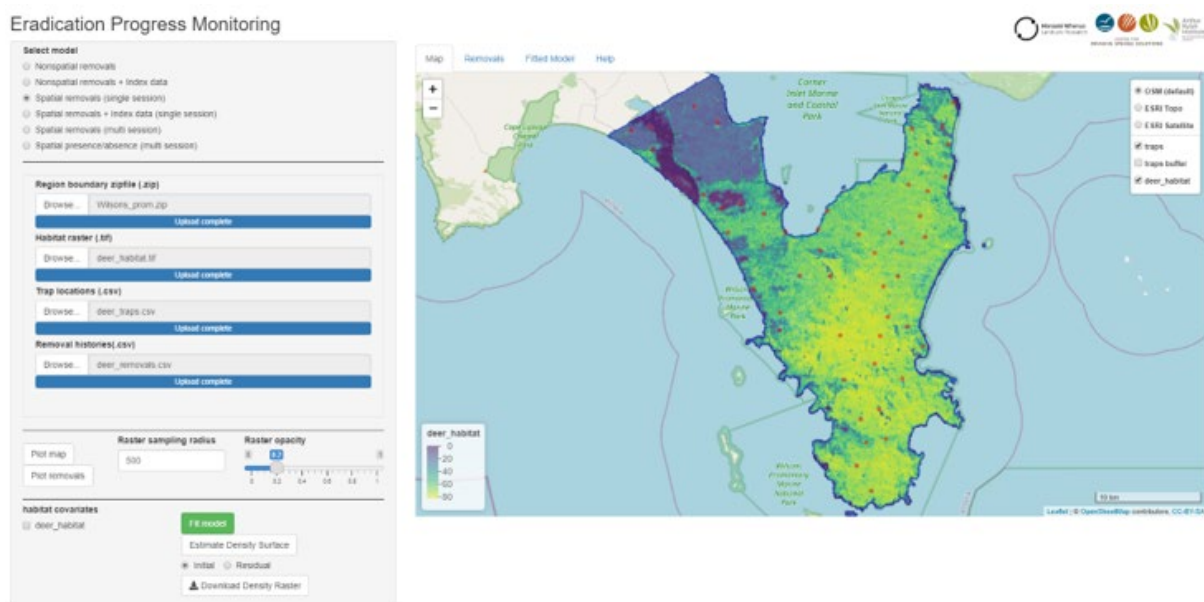


Figure 7. Screenshot of the eradication progress decision-support tool



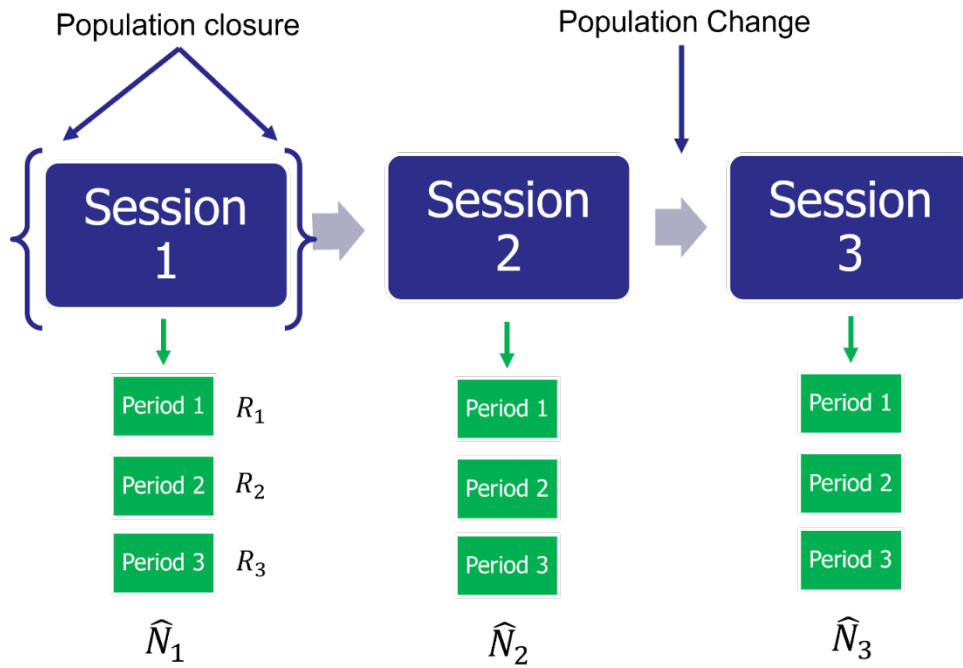


Figure 8. Structure of the temporal relationship in the data collected during eradication activities where pest individuals are removed (e.g. trapping or hunting). Here data on pest removals  $R$  are collected for three discrete sessions, each with three periods of removals. Population abundance  $\hat{N}$  within each session only changes due to the active removal of pest individuals but is subject to natural additions or losses between sessions.

For valid estimates of population size to be obtained from records of pest removals and associated control effort, the removal method(s) must be able to remove individuals at a rate that causes a noticeable population decline. This can be easily visualised using a cumulative catch curve (Figure 9), which plots the cumulative catch (removals) of individuals against the catch-per-unit effort (CPUE), combined over sessions. 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), the population might not be reducing at a rate high enough to achieve eradication, or 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 9 assumes that detectability is constant for the duration of removal activities, but the residual population may actually no longer be susceptible to the removal method (e.g. they may be trap-shy and therefore never get caught, resulting in detectability declining to zero). Recognising 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).

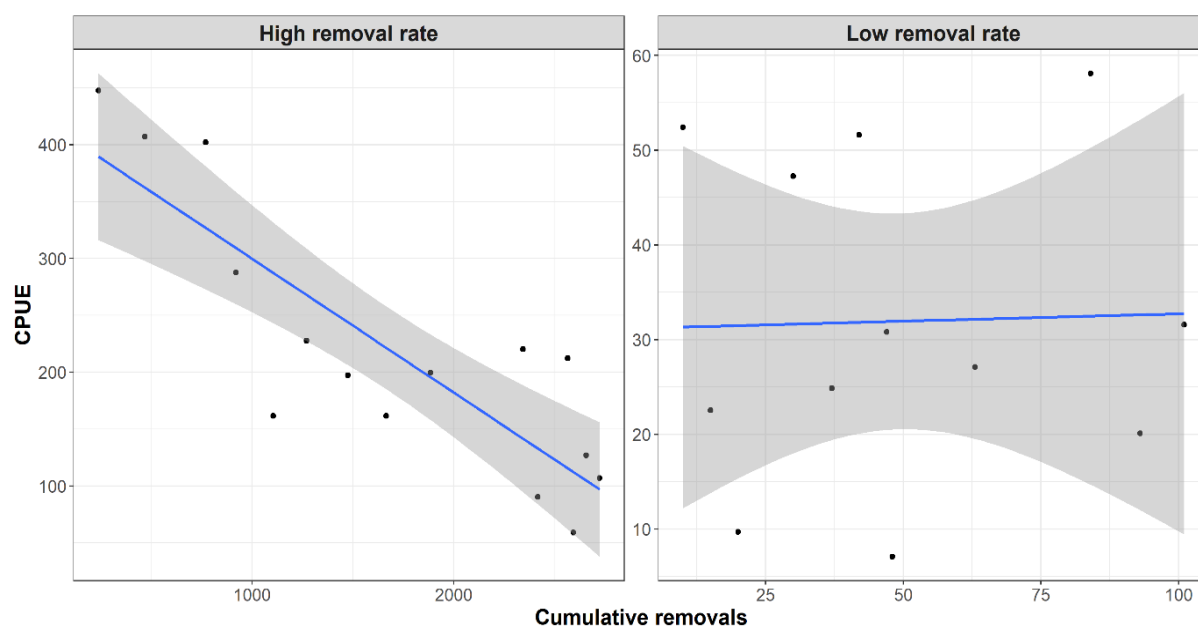


Figure 9. Plot of the cumulative catch (removals) of individuals vs the catch-per-unit effort for two hypothetical eradications with a high or low removal rate.

In general, the eradication progress decision-support tool relies on four different types of data: (a) spatial data of the region of interest, (b) spatial data for variables that might influence habitat preferences of the pest species, (c) locations of removal devices (i.e. trap locations), and (d) records of the number of pest removals for each location, session and period. The tool also caters for aspatial data, which does not require device or pest locations. Aspatial data is usually collected during search-encounter type removals where there are no set device locations (e.g. aerial shooting from a helicopter). All models used here require data from at least three periods within a session. Each of the data model types available within the eradication progress decision-support tool are outlined below, with example data shown for each model type.

## SPATIAL DATA

### REGION BOUNDARY FILE (.SHP, .GPKG)

Information is required about the region of interest where the eradication operation is being undertaken. The minimal requirement is geospatial vector data of the region boundary either in Esri shapefile format, packaged in a .zip file or in the non-proprietary GeoPackage format (\*.gpkg). The boundary can comprise single or multiple polygons and can contain 'holes' (i.e. due to the presence of non-habitat, such as a lake). The region should be in a projected coordinate reference system with units in metres (m) (e.g. Figure 10).

### HABITAT RASTER FILE (.TIF)

Information on biophysical variables that might influence pest densities can be important in helping delineate areas of potential high risk of infestation by the pest species. This information can be supplied in the form of one or more raster files, one for each variable. Habitat rasters can also comprise derived variables, such as outputs from species distribution models. Raster data should be supplied in GeoTiff format (\*.tif) using the same coordinate reference system as the region shapefile above with units in metres (e.g. Figure 10). The raster can be any resolution; however, care should be taken for large regions with a small resolution because they may result in large files that overwhelm available memory.

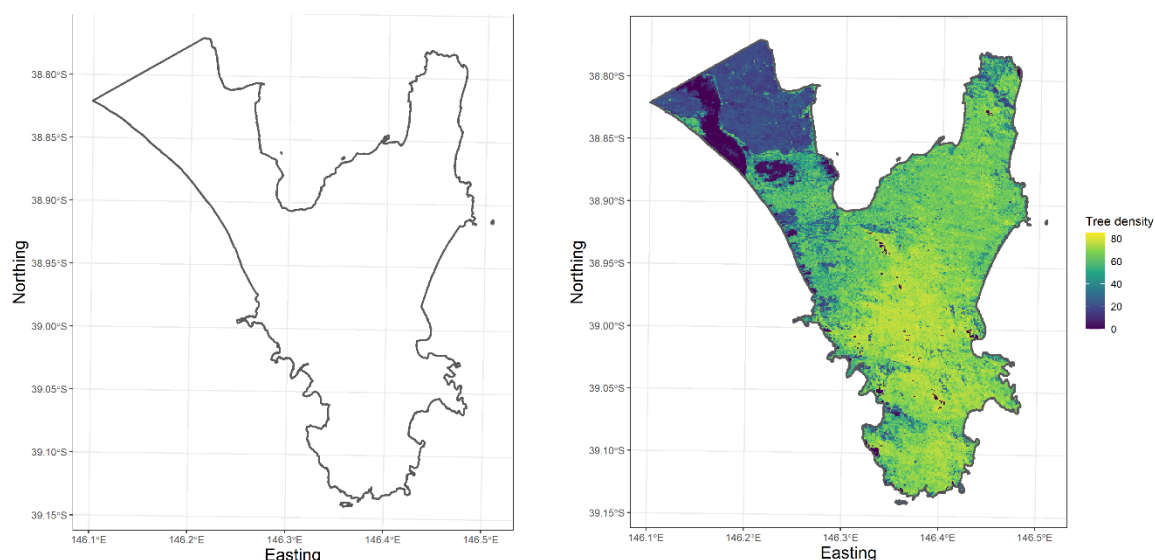


Figure 10. Example region boundary shapefile (left) and raster data on tree density. Resolution of the raster is 100 m, and the coordinate reference system is VicGrid GDA94 (epsg code 3111).

## MODELS

Models have been developed to analyse removal data that has been collected from either spatially referenced devices (e.g. traps) or where removals are not spatially referenced (non-spatial removals). Both single and multiple session data are catered for, and models can additionally incorporate index data that has been collected contemporaneously with the removal data (Figure 11).

## Eradication Progress Monitoring

Select model

K

☒ Nonspatial removals  
☐ Nonspatial removals + Index data  
☐ Spatial removals  
☐ Spatial removals + Index data  
☐ Spatial presence/absence

Figure 11. Model types available in the Eradication Progress decision-support tool

In addition to the analysis of removal data, models have also been developed to analyse presence–absence data collected from a set of spatially referenced sites. A more detailed overview of each model type available in the tool is given below. All models are also available through the standalone R package ‘eradicate’ available at <https://github.com/eradicate-dev/eradicate>.

- Non-spatial removals (single or multisession):** This model implements the catch-effort model of Gould and Pollock (1997). It is an aspatial model, which means that device/method and pest 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 or location, separately for each session. Effort data is calculated as the number of devices set or time/distance searched in each session. The required data should be entered into a spreadsheet (.csv file) with columns ‘catch’, recording the removals for each period; ‘effort’, recording the trapping/search effort during the period; and optionally ‘session’, recording the session number (for multisession data). If data are for a single session, this column can be omitted (see below).
- Non-spatial removals + index data:** This model is the same as the non-spatial removal model detailed above but also allows additional monitoring data (index data) to be included. The index data can be any index of abundance (e.g. number of detections on a camera, etc.).

Index data can be useful for detecting the presence of individuals when the removal methods fail to detect any. Hence index data can be valuable as a foil against capture heterogeneity affecting the primary removal method. The idea is that the index should decrease proportionally as pest density decreases due to the removal method. Index data and its associated effort (e.g. camera nights) should be included as extra columns labelled index and effort, respectively.

- **Spatial removals data:** This model implements the multinomial removal model (Haines 2019) for data collected from either single or multiple sessions. Unlike the non-spatial model, device locations are required for this model, and habitat information can be used to model spatial variation in initial abundance. The removal data should be in a spreadsheet (.csv file) with removals for each period in columns and devices in rows. Hence, an operation using 50 traps set for six nights would have corresponding removal data organised in 50 rows and 6 columns. Multisession data has a similar format to single session data but contains an additional column session. An additional spreadsheet (.csv file) recording the locations of each device is also required. This dataset should have device locations coordinates with X (easting) and Y (northing) in the first and second columns, respectively. The coordinate reference system should be the same as the shapefile of the region boundary. This dataset should also have the same number of rows as the removal data.
- **Spatial removals + index data:** This model estimates the generalised removal model of Dorazio et al. (2005) for removal data collected from either single or multiple sessions. However, it also has the facility to analyse both removal data and additional index monitoring data collected in parallel with the removal data. The index data are assumed to be derived from monitoring devices set in the same general vicinity (or a subset thereof) as the removal devices (e.g. camera traps). Hence, the index data should have the same number of rows and columns as the removal data and are uploaded into the tool using the detection histories button. Any index of abundance derived from these detection data would be suitable to use as index data. Removal locations without an associated index monitoring device should have the corresponding row in index detections left blank.
- **Spatial presence/absence data (multisession):** This model analyses spatial removal data from multiple sessions using the dynamic occupancy model (MacKenzie et al. 2003). Either presence/absence data or an index (count) at each device location is required for this model. Index data are truncated to 0/1 before analysis. The model estimates the probability of occupancy or the proportional use of a location or sampling unit. It is most useful for those species where a direct estimate of abundance is not feasible (e.g. invasive ants occupying an area divided into grid cells). The multisession presence/absence data has a similar format to the multisession spatial removal model (see below). Trap location data format is also similar to the single session spatial model.

All these models provide estimates of the initial abundance of the pest species (i.e. before the start of the eradication activities), separately for each session, as well as the residual abundance (abundance following eradication activities in the final session). As more eradication sessions are conducted, the updated detection history files should be uploaded into the tool and revised estimates obtained. The app also contains an associated help file summarising the functionality of the app.

## WORKED EXAMPLES

**Non-spatial models:** This analysis is of a fictional dataset for an eradication program on rabbits (*Oryctolagus cuniculus*). The data give the numbers of rabbits removed by shooting over five sessions with each session consisting of eight removal periods. A total of 923 rabbits were removed, and the full data are reproduced in the example data available online at Zenodo (Ramsey et al. 2022). Analysis of these data with the non-spatial catch-effort model indicated an initial population estimate of 835 rabbits and a residual abundance of 1 rabbit (Figure 12: 'Abundances' tab). Of note was that the estimate of the initial abundance (835) was less than the total number of rabbits removed (923). However, since data were collected over multiple sessions, the rabbit population was assumed to be open to natural additions or losses between removal sessions. Hence, the rabbit population could have increased between each session due to breeding and/or immigration. Since we are mainly interested in the session-specific abundances, the model used here does not attempt to estimate the

contributions to the population due to these natural additions or losses as the net changes due to these processes are reflected in the removal data.

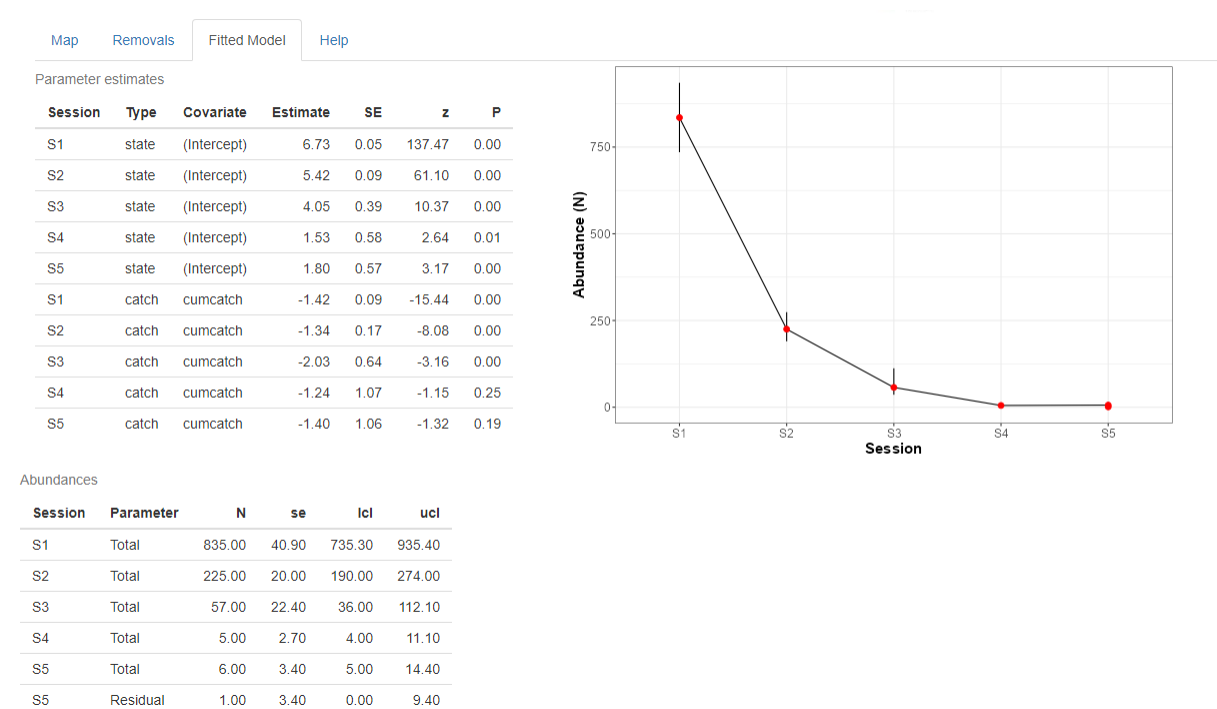


Figure 12. Analysis of a non-spatial, multisession removal dataset on the rabbit removal data (Ramsey et al. 2022) using the Eradication Progress decision-support tool. Parameter estimates provide the estimate of the (log) abundance for each session and the catch coefficient for each unit of search effort (cloglog scale).

## SPATIAL MODEL

The next example presents an analysis of a fictional dataset on hog deer (*Axis porcinus*) removal from Wilsons Promontory National Park. Deer were removed by trapping (clover traps) at 50 locations across the park (Figure 13) over eight sessions with traps set for five consecutive days per session (i.e. five removal periods per session). Habitat information in the form of a raster file of tree density was also available for the park with the average tree density within a 1 km radius of each trap used as a covariate in the model (Figure 13). Analysis indicated that the initial population of deer was 811, with 15 deer remaining following the final trapping session (Figure 14). Deer abundance was positively related to tree density with a parameter estimate of 0.02 with higher relative abundance of deer located towards the centre of the park (Figure 15).

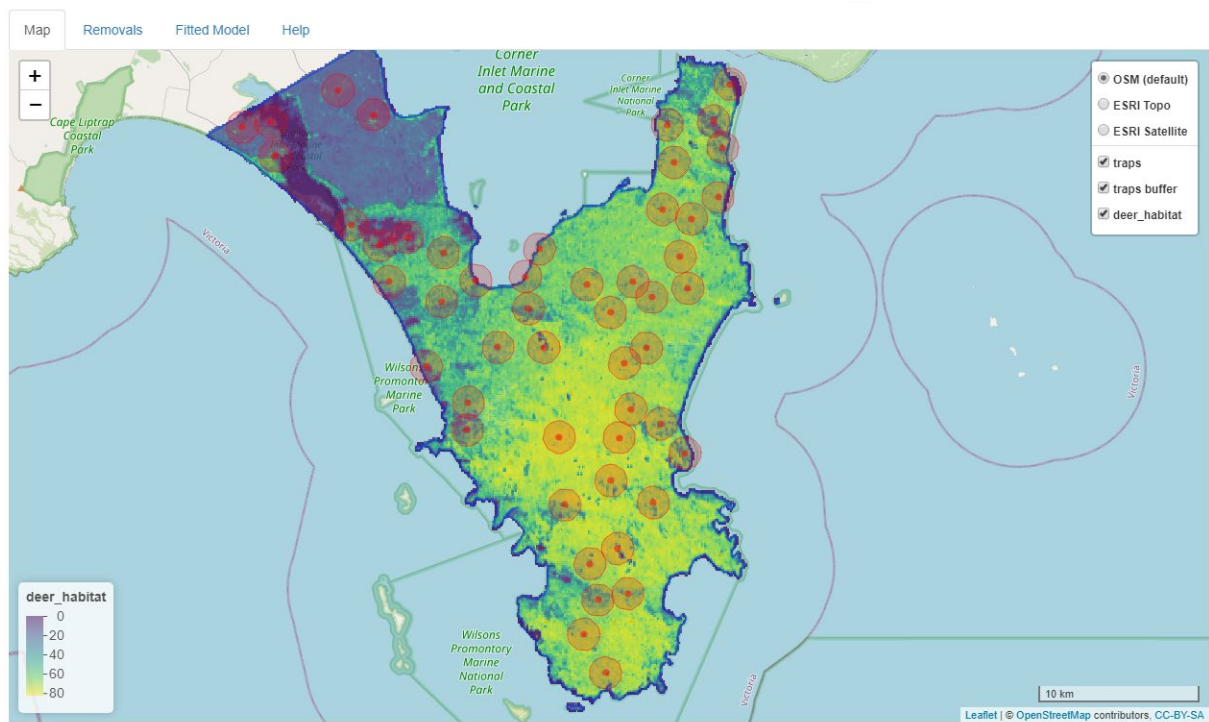


Figure 13. Fictional dataset of the removal of hog deer from Wilsons Promontory National Park by trapping. Habitat information for the park was given by a raster file of tree density, which varied from 0 to 80 trees/ha (blue-green-yellow gradient). Trap locations are indicated by dark red circles buffered by 1 km, indicating the radius where habitat information was extracted for each trap and used as a covariate in the model.

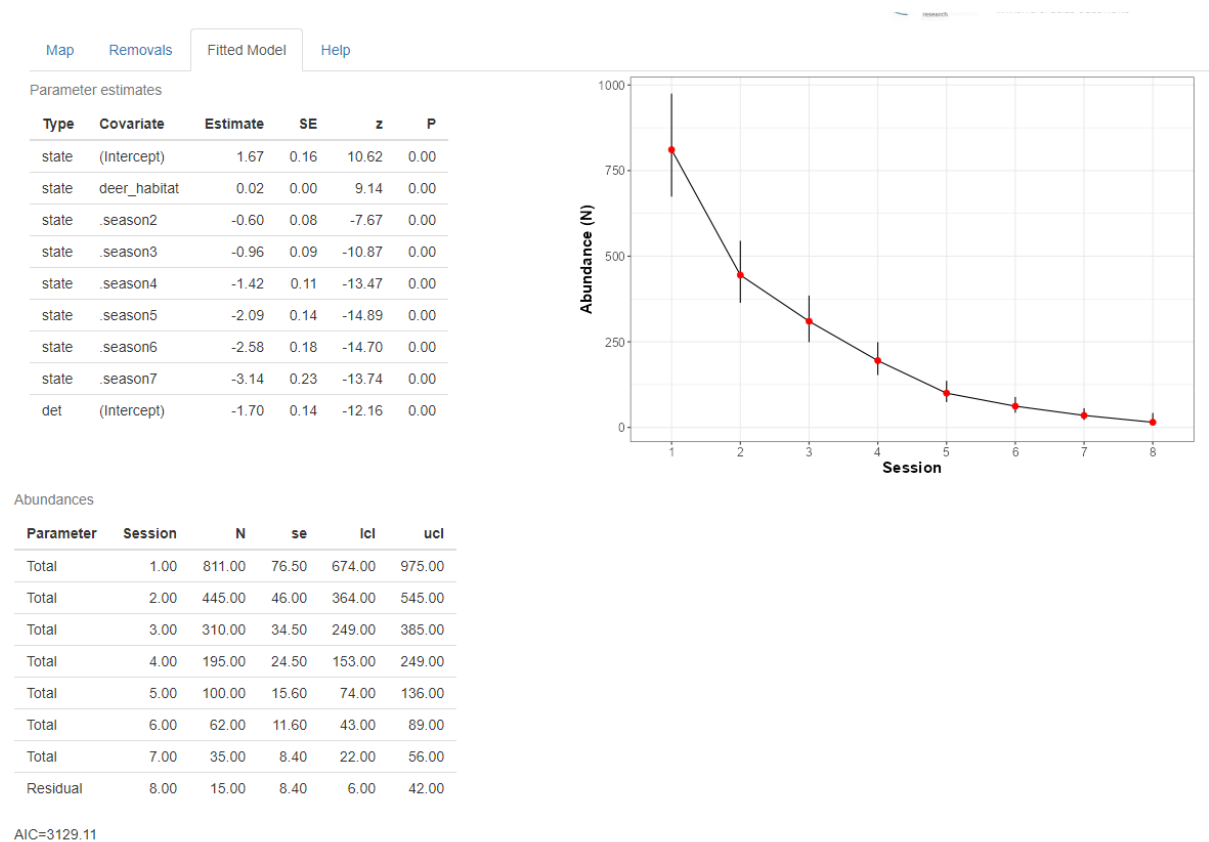


Figure 14. Analysis of a spatial, multisession removal dataset on the rabbit removal data (Ramsey et al. 2022) using the Eradication Progress decision-support tool. Parameter estimates provide the estimate of the (log) abundance for each session and the catch coefficient for each unit of search effort (cloglog scale).



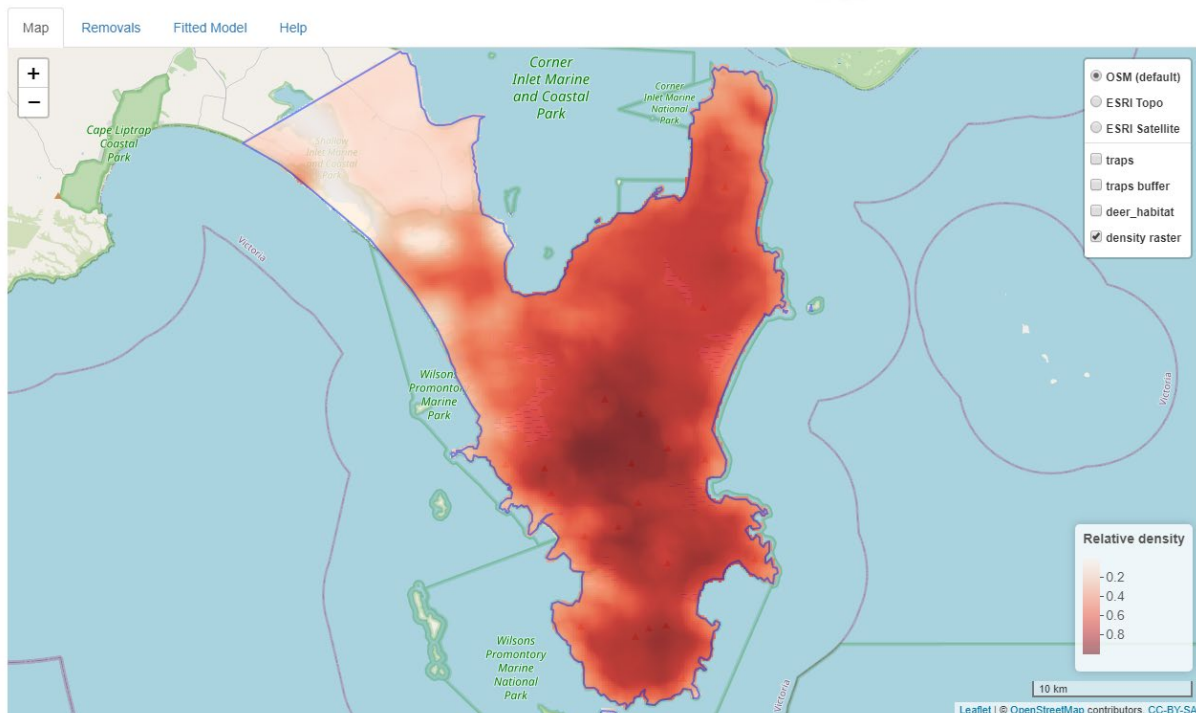


Figure 15. Raster of the relative initial abundance of deer estimated by the model

## EVALUATION PHASE

### PRINCIPLES FOR PROVIDING CONFIDENCE OF 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 an infallible detection method. 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 (Ramsey et al. 2009; Ramsey et al. 2011; Samaniego-Herrera et al. 2013). This section presents the framework behind quantitatively assessing eradication success 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.

Once pests are no longer being detected, a surveillance phase is implemented to look for any individuals that may have survived the control phase. If there is any evidence of the pest, the overall control operation has not been successful and eradication cannot be declared (assuming there are no false positive detections). If no individuals are detected, it does not necessarily mean the pest is absent from the area as individuals may have survived yet remained undetected.

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

- the level of confidence in eradication before doing surveillance (i.e. how good was the control program?)
- the search for pests that may have survived the eradication phase (i.e. how good was the surveillance network?)

Probabilities can be used to quantify these confidence levels with Bayes' theorem as follows:

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

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 the

detection/surveillance network is. Bayes' theorem updates prior knowledge (*Prior*) with data (*SSe*) to give the posterior probability of absence (*PoA*<sup>1</sup>).

Armed with Bayes' theorem, a *Prior* and the efficacy of the surveillance network (*SSe*; see Anderson et al. 2022), *PoA* can be calculated then a management decision made as to whether to declare eradication or not. If the calculated *PoA* it is not high enough, more surveillance can be conducted to increase *SSe* until a suitable value of *PoA* is reached. 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. This tool is available at <https://landcare.shinyapps.io/proofofabsence/>.

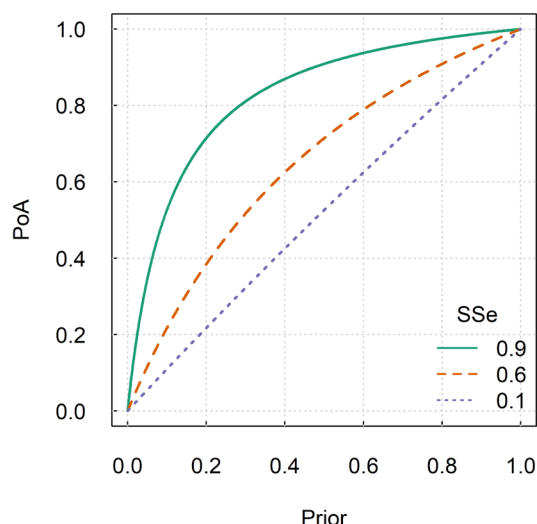


Figure 11. Contour plots showing the relationship between the *Prior* (x-axis) and the resulting *PoA* (y-axis) for three levels of *SSe* (contour lines)

## SPECIFYING THE *PRIOR*

As shown in Figure 16, 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 confidence that control was sufficient to eradicate the pest is low (*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%).

As described above, specifying the *Prior* is an important task, with a range of methods, including:

- In the absence of any information, specify a default *Prior* from a BetaPERT distribution with a mean of 0.5, min = 0.1 and max = 0.9. This *Prior* allows for uncertainty around the prior probability of absence, with a broad, plausible range of probabilities between 0 and 1, and has an expected value of 0.5, reflecting a neutral opinion about the true presence.
- Seek expert opinion from a single or multiple experts about the *Prior* distribution using an elicitation approach (Ramsey et al. 2009).
- Use 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.

<sup>1</sup> Reminder: As noted before, any positive detection during surveillance indicates that eradication has not yet been successfully achieved.

- 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).
- Combine the previous approaches by obtaining an expert judgement that is informed by their knowledge of similar control operations, the modelled simulations and other factors (e.g. risk of reinvasions).

## 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 (Warburton and Gormley 2015). 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 control if the eradication fails. Sociopolitical factors should also be considered, such as what is the 'cost' associated with loss of public acceptance in the program or loss of reputation if success is declared incorrectly? If this cost is high, it may 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 tuberculosis freedom in wildlife. In theory this implies that 1 in 20 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.  $PoA = 0.99$ ).

## FINDING SURVIVORS: WHAT IS THE WORST-CASE SCENARIO?

In the context of surveillance to confirm eradication success, survivors may be detected. The question then changes from 'What is the confidence that eradication has been achieved?' to 'What is the residual population abundance, given survivors have been detected?' Calculating the residual abundance is described above, 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). The following equation can be used 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 ( $P(N \leq Y|n)$ ):

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

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, confidence that the residual population abundance is  $\geq 12$  is 95% (Figure 17).

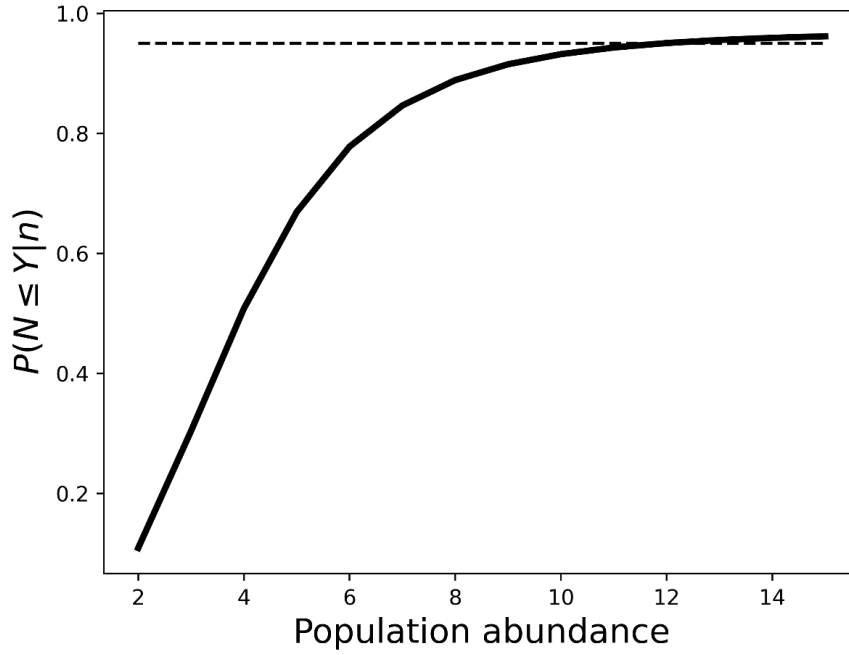


Figure 12. Probability that the residual population abundance ( $N$ ) is less than or equal to  $Y$  ( $P(N \leq Y|n)$ ). In this example  $SSe = 0.33$ , number of detected animals ( $n$ ) = 2, and target level of confidence = 0.95 (dashed horizontal line).

## 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. However, insufficient surveillance can allow survivors in the pest population to reproduce into a large and renewed widespread problem. Quantitative planning increases the chances of deploying a cost-effective surveillance strategy.

The level of surveillance required ( $SSe_{Req}$ ) to move the level of confidence in eradication from the *Prior* to the target  $PoA$  can be determined as follows:

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

For example, if  $Prior = 0.9$  (i.e. 90% sure of eradication success after control efforts) and  $PoA_{Target} = 0.95$  (i.e. the aim is to be 95% sure of success), then  $SSe_{Req} = 0.53$ . This means that enough surveillance needs to be conducted to have a 53% chance of detecting any individual remaining if one were present (Figure 18). If, however, the aim is to be 99% sure of absence, then a much higher level of surveillance would be needed for the same  $Prior$  (i.e.  $SSe_{Req} = 0.91$ ).

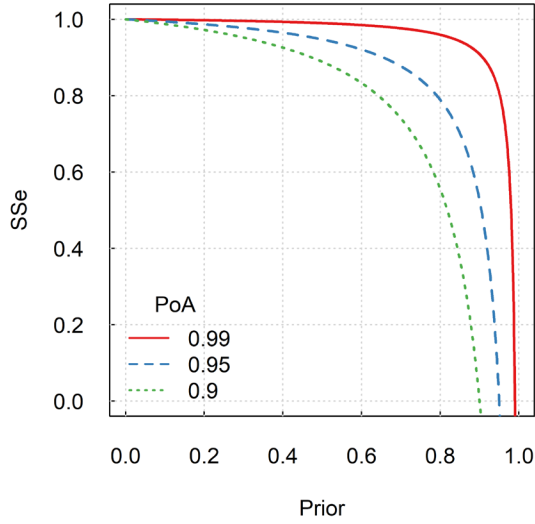


Figure 13. Contour plots showing the relationship between the Prior (x-axis), the PoA (contour lines) and the SSe (y-axis)

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,  $\sigma$  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:

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

## PROOF OF ABSENCE DECISION-SUPPORT TOOL

The web-based Proof of Absence decision-support tool (Figure 19) allows eradication managers to analyse surveillance data to quantify a posterior probability that a target species is absent, given no detections have occurred. The tool uses the Shiny web application development package (Chang et al. 2022) within the R language (R Development Core Team 2020). The app is available at <https://landcare.shinyapps.io/proofofabsence/>. It has a user-friendly point-and-click interface for uploading data and set parameter values. It can accommodate any species and any spatial scale (extent and sampling unit). Internal functions used in the app are structured as an R package called 'proofofabsence', available at <https://github.com/eradicate-dev/poaShiny>. Functions used in the package were originally written in the Python language, and calculations for the package call these Python scripts using the 'reticulate' R package (Ushey et al. 2022). Pre-processing and post-processing steps have been replaced by equivalent R functions.

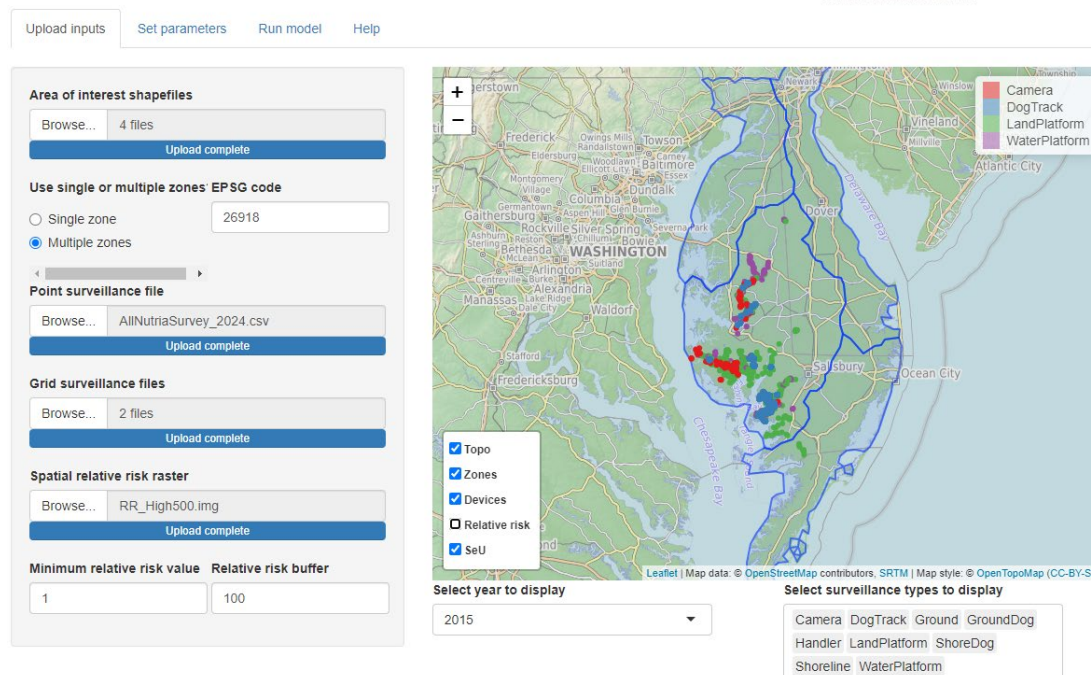


Figure 14. Screenshot of the Proof of Absence decision-support tool

The modelling approach superimposes a grid-cell system on the area of interest (extent). The grid cells correspond to the sampling unit discussed above. Sampling units should be much smaller than a typical home range of the pest species. Each sampling unit is characterised by a relative risk of where a pest could survive in the landscape and/or where an immigrant pest could settle after incursion into the area of interest. Two general types of surveillance data can be analysed by the model: point detection devices and grid-cell surveillance. Point detection device surveillance data are the locations of devices and their type. Grid-cell surveillance data are the searched grid cells over the extent being eradicated. 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 modelled as 'point devices' (Anderson et al. 2022). 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. Grid-cell surveillance data quantifies the search effort within each grid cell. This is useful when the exact spatial details of surveillance are not known. Some examples are time that hunters spent in a grid-cell area, or public reporting of target-species sightings (Anderson et al. 2022).

Point detection device and grid-cell surveillance data both require parameters that describe the probability of detecting a surviving pest. For point detection devices, these parameters are the mean and standard deviation for  $g_0$  (the nightly probability of capture of an individual by a surveillance device placed at the centre of the animal's home range) and  $\sigma$  (the spatial decay parameter for a half-normal home-range kernel, to model the decline in detection probability with distance between the home-range centre and the detection device). Grid-cell surveillance data uses the mean and standard deviation of the probability of detection over the surveillance period.

The tool uses four different types of spatial data: (a) the boundaries of the area of interest, (b) the location of the surveillance devices, (c) grid-cell surveillance data, and (d) an optional grid of relative risk of pest survival or immigrant settling after control (Figure 20).



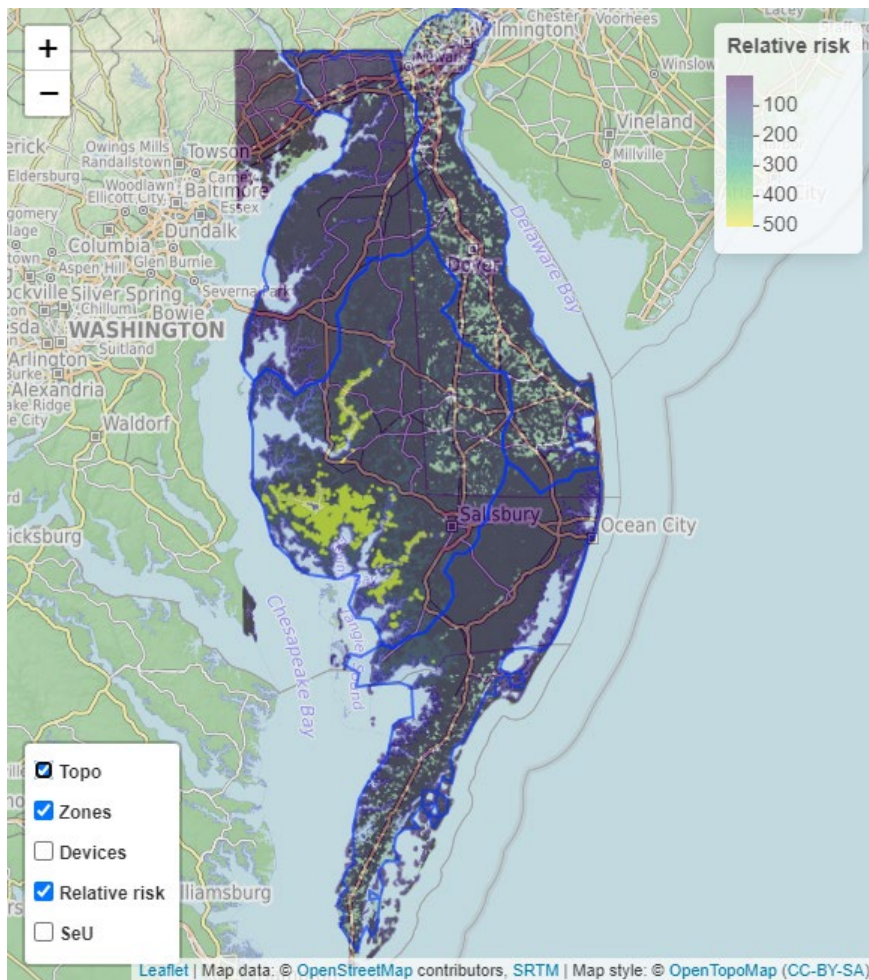


Figure 20. Screenshot of a relative risk raster displayed using the Proof of Absence decision-support tool

The model outputs summary figures, tables and maps of model estimates. These summaries are generated when models are completed and can be viewed in the app or exported to a zip file. *PoA* estimates are shown graphically or as a summary table alongside means and 95% credible intervals for each session (Figure 21).

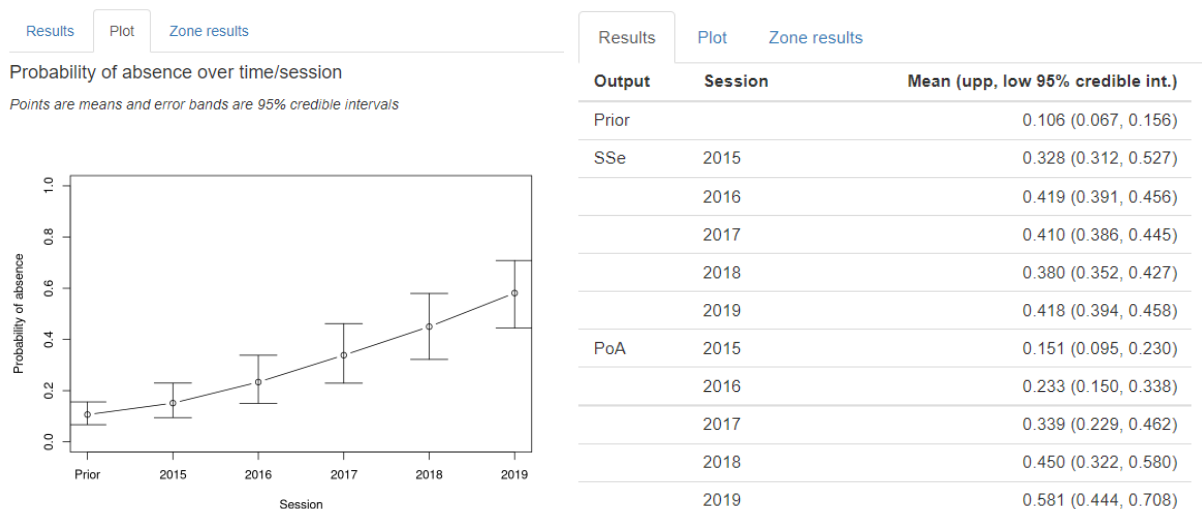


Figure 21. Screenshot of PoA estimates over time displayed using the Proof of Absence decision-support tool. System-level surveillance sensitivity (SSe) estimates are included in the table output.

## Proof of absence & sensitivity estimates

Results   Plot <b>Zone results</b>		
Year/session	Zones	Mean SeZ (upp, low 95% credible int.)
2015	BlackWater	0.3649 (0.3538, 0.4951)
	Finger	0.0931 (0.0511, 0.6230)
	Maryland	0.0651 (0.0000, 0.8634)
	Delaware	0.0706 (0.0000, 0.9077)
2016	BlackWater	0.4482 (0.4348, 0.4675)
	Finger	0.1842 (0.1070, 0.2881)
	Maryland	0.2576 (0.0901, 0.4588)
	Delaware	0.2786 (0.0770, 0.5107)

Figure 22. Screenshot of zone-level sensitivity (SeZ) estimates over time and for each zone displayed using the Proof of Absence decision-support tool

If a broadscale eradication approach is used (Figure 2; Anderson et al. 2022), then a summary table of zone-level sensitivity estimates (SeZ; Figure 22) can be shown for each zone and for each session (if multiple sessions are used). The tool can also display the mean sensitivity associated with individual sampling units (SeU). This is stored as a raster and can be displayed on the main map on the input tab (Figure 23). Display of the map is optional because it uses the resolution values set by the user, which can be small, potentially producing very large files which cannot be displayed.

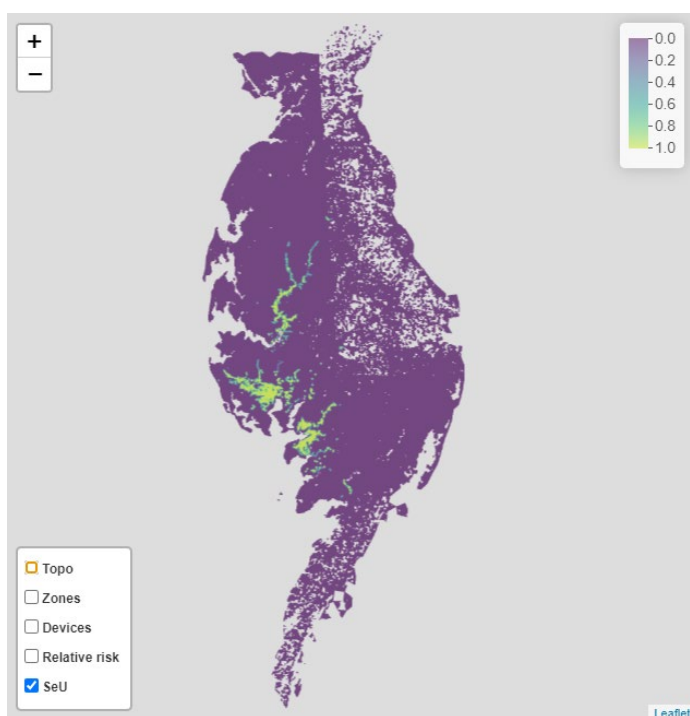


Figure 23. Screenshot of mean sampling-unit sensitivity (SeU) map displayed using the Proof of Absence decision-support tool

Finally, the tool provides the option to export a .zip file of model outputs. Exported files contain the same information used to create the display in the app but allow users to customise tables and maps for their own reporting. Summary tables are exported as .csv files, and spatial information (area of interest boundaries, relative risk and mean sampling-unit sensitivity) is exported as raster (.tif) files.

## END-USER FEEDBACK

Two workshops demonstrating the functionality of the decision-support tools were held with potential end users. The first workshop was held in Christchurch NZ, 17–18 October 2019, which specifically covered concepts on demonstrating proof of absence. The second workshop was held in Melbourne, 17–18 May 2022 and covered the complete suite of tools developed during this project (Figure 24). These workshops identified information gaps and software modifications that could be implemented to improve the functionality and usability of the tools. During the second workshop a number of improvements were identified. At the time of writing, the majority of these have now been incorporated into the software tools. However, some issues remain, including need for:

- improved documentation and in-app help (partially complete)
- a list of accepted parameter values for the most common detection devices for an array of pest species, required by the Eradication Feasibility and Proof of Absence decision-support tools
- a list of accepted population growth parameters required by the Eradication Feasibility decision-support tool
- ability for the Eradication Feasibility decision-support tool to upload a file of predetermined device locations
- improved error handling for the Eradication Progress decision-support tool, including more informative messaging that the data are inadequate for the selected model.



Figure 24. Participants in the second eradication tools workshop for end users, May 2022

# CONCLUSIONS

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 and ongoing financial cost of minimising 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 is inherently difficult and 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, policymakers, managers and the public.

Policy and management decisions associated with the eradication process are divided into three phases: (a) assessing feasibility and planning control strategies, (b) assessing progress (and revising strategies), and (c) assessing and confirming absence of the pest species. In this project, we have developed general methodologies and models for providing objective support for these decision processes. 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. While every effort has been made to make these tools robust and user friendly, things can still go wrong. Models fitted to sparse data or data that violates the main assumptions of these models can give incorrect answers. Therefore, managers are advised to seek quantitative support when using these tools.

This project has developed important tools and made them freely available online. They are tailored for end users and use a point-and-click graphical user interface. Tools have been developed for each of the three phases of an eradication response (Figure 1). The Eradication Feasibility decision-support tool allows the assessment of the efficacy and cost-effectiveness of different control strategies for achieving eradication (phase 1). The Eradication Progress decision-support tool allows analysis of typical data collected during the deployment of eradication programs to enable estimates of residual pest population size and rate of removal (phase 2). Lastly, the Proof of Absence decision-support tool allows eradication managers to quantify the probability of absence (*PoA*) for a pest species given no detections have occurred (phase 3). 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 decision-support tool is flexible in that it can accommodate multiple surveillance methodologies and complex ecological attributes.

The availability of these online user-friendly tools creates 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.

## NEXT STEPS: MAINTENANCE, FOCUS ON INNOVATION FOR FUTURE RESEARCH

Currently the web-based tools are hosted at <https://landcare.shinyapps.io/>, which is a domain maintained and curated by Manaaki Whenua Landcare Research. Ongoing maintenance of these apps will be required to ensure that they remain fit for purpose. The immediate priorities for maintenance should include the list of improvements identified by end users that remain outstanding, as incorporation of these suggested modifications should improve the functionality and ease of use of the software tools. In addition, ongoing maintenance will be required to incorporate any changes to downstream package dependencies that otherwise will inevitably lead to the tools rapidly going out of date and/or result in the gradual introduction of errors or bugs. There is some current interest in incorporating these tools into a new biosecurity software platform, Biosecurity Commons (<https://www.biosecuritycommons.org.au/>), that is being developed by the University of Melbourne and Griffith University, in partnership with the Queensland and Australian governments. Incorporation of these tools into that platform could ensure a long-term solution to ongoing maintenance issues.

Future research should ensure that the functionality of these tools remains up to date, by incorporating the latest innovations in detection and monitoring theory relevant for informing pest eradications. For example, future improvements to the Proof of Absence decision-support tool could incorporate the latest analytical Bayesian solutions to provide compact and rapid estimates of the most cost-efficient survey effort for quantifying proof of absence (Barnes et al. 2021; Barnes et al. 2022).



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*Note: bold references indicate project outputs. Other CISS and IA CRC publications are marked with an \**

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