Framework for undertaking eradication programs on insular populations of vertebrate pests

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2 authors, including:

David Will
Island Conservation

Department of Sustainability and Environment

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David Ramsey and David Will

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State Government Victoria

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David Ramsey[1] and David Will[2]

[1] Arthur Rylah Institute for Environmental Research
123 Brown Street, Heidelberg, Victoria 3084

[2] Island Conservation
100 Shaffer Rd, Long Marine Lab, Santa Cruz, CA 95060, USA

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Arthur Rylah Institute for Environmental Research
Department of Sustainability and Environment
Heidelberg, Victoria

Report produced by: Arthur Rylah Institute for Environmental Research
Department of Sustainability and Environment
PO Box 137
Heidelberg, Victoria 3084
Phone (03) 9450 8600
Website: www.dse.vic.gov.au/ari

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1 Summary

We propose a general framework to address eradication of vertebrate pests from islands where the pest population is progressively reduced to zero through a succession of removal events (i.e. trapping, hunting, etc.). Such an eradication program typically has three phases. Phase 1 is a pre-implementation phase, in which data essential for updating and monitoring the success of the program are collected prior to the start of eradication activities. Phase 2 is the implementation of the eradication program, in which the population is progressively reduced to the point where individuals can no longer be detected. This phase includes the targeted collection of data that will be used to update the tactics and methods used as the population is reduced to low levels. Phase 3 involves conducting decision support using existing data and additional surveillance to confirm eradication has been achieved. This last phase may continue until some 'stopping rule' is reached and, assuming no pests are detected, the eradication program is then declared a success (Ramsey et al. 2011).

This framework is not intended to apply to eradication programs that rely on a single control event (e.g. aerial baiting) that either achieves eradication or fails on the day. However, the framework can still be used where broad-scale control is used to achieve a large initial reduction in the population (e.g. aerial baiting). In this instance the framework can be implemented immediately following the initial knock down event. We discuss this issue further in Section 4.

1.1 Purpose

The purpose of the framework is to provide eradication project managers with near-real-time analyses of data collected during the eradication program, to allow them to make optimal (i.e. cost-effective) decisions regarding the deployment of resources and application of methods to achieve eradication of an island pest population with a specified level of confidence.

More specifically, this tool can model the efficiency and costs of an eradication program and assist in forecasting the amount and duration of effort required to remove all remaining target animals. The framework could also identify the amount and duration of effort needed to have the desired level of confidence that the eradication is complete (i.e. evaluation of null detections). This entails the use of different techniques and models before, after, and during the course of the eradication program and would ideally be able to incorporate information collected in near-real-time. Coupled with digital data collection, this tool would be able to automate data flow from field entry to model output, increasing the speed that information is available to managers.

Ultimately, the purpose of the framework is to provide both guidelines and a tool that will give field managers access to information about the progress of the eradication, the amount of effort required to finish the job, and an elevated level of confidence that the project has been successfully completed. We anticipate that these tools will increase the likelihood of eradication success and reduce total eradication cost by providing a statistical understanding of eradication progress and a metric for completion.

The eradication framework (Figure 1) outlines a number of connected steps that are logically followed during the course of an eradication program.

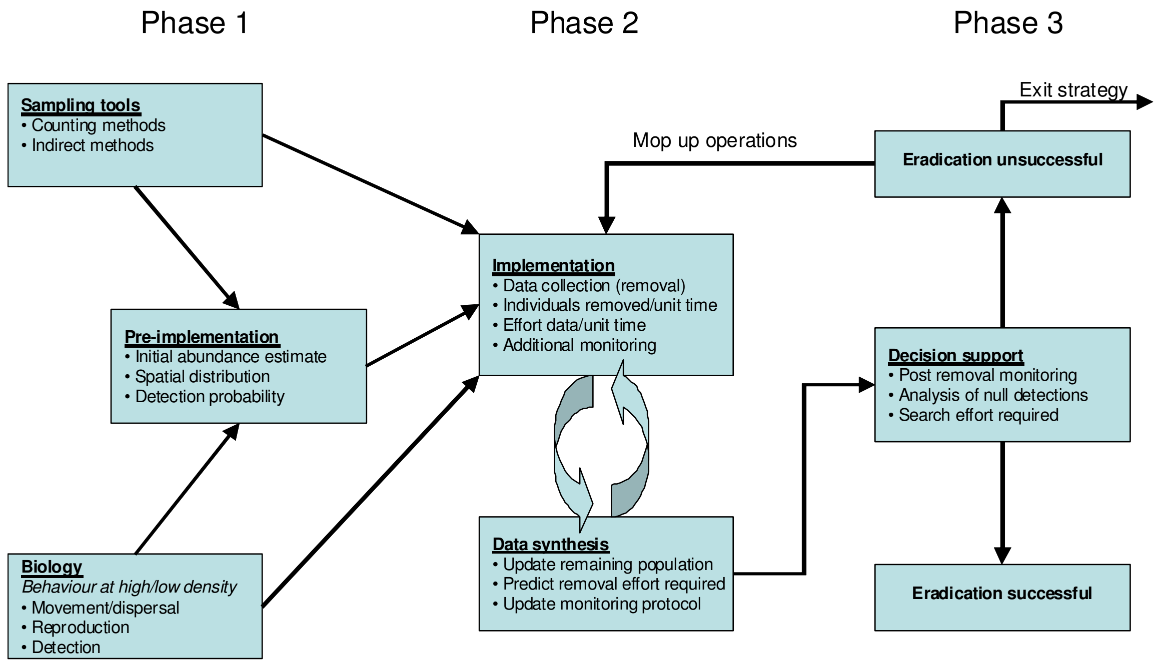

Figure 1. The island eradication framework for vertebrate pest species.

2 Initial considerations

2.1 Biology of the target species

Before initialising the pre-implementation stage of the program, some consideration of the species targeted for eradication is required. The biological parameters of the target species, in terms of reproductive biology, life history and dispersal ability need to be considered to determine the likely feasibility of the eradication program (Myers et al. 2000; Simberloff & Rejmanek 2011). High dispersal or reproductive rates can seriously hinder an eradication program by allowing a rapid recovery or re-invasion by the target species. The removal methods must also be able to remove the very last individuals in the population, otherwise the eradication program will fail. Often this can be exacerbated by changes in the catchability or detectability of the target animals because they have an innate or learned avoidance behaviour that affects a particular removal method. Identifying changes in catchability are therefore essential for deciding when to switch to alternative methods to remove the last individuals. Hence, there are three conditions that must be met in order for an eradication program to succeed (Bomford & O'Brien 1995):

1. All individuals must be at risk of being caught or detected by the removal method(s).
2. Immigration (and hence re-invasion) must be prevented.
3. Individuals must be removed faster than the rate of births.

In addition, consideration must also be given to the potential ecosystem-level effects of removing the target species. The benefits of the eradication program will be compromised if the removal of the target species results in the unintended increase of another exotic species, which could lead to other undesired impacts. Other undesirable effects that need consideration are potential impacts of the removal methods on non-target species.

2.2 Sampling tools

The array of methods used for sampling the target population can be divided into two main types.

Count methods

These involve counts of individuals using either visual methods (e.g. line transect sampling, point counts) or capture (e.g. trapping, hunting). Count methods 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

$$\hat{N} = \frac{C}{\hat{p}} \qquad \text{[Equation 1]}$$

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. In the main, there are three basic approaches for estimating the detectability parameter p and thus the size of a closed population (Borchers et al. 2010):

- Use changes in the number detected as some feature of the survey changes (e.g. line transects, point counts).
- Use changes in the number detected as individuals are progressively removed (e.g. removal methods, change in ratio methods).

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

Since our framework will apply only to eradication programs that use trapping or hunting techniques, which progressively remove individuals from the population, we will be concerned primarily with approach 2. However, approaches 1 or 3, or both, will usually be used in the pre-implementation stage in order to get an estimate of initial population size (see below). Comprehensive reviews of these approaches are given in Williams et al. (2002) and Borchers et al. (2010).

Consideration of the primary removal method is of great importance because the results will also 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 (Figure 2), which plots the cumulative catch of individuals against the cumulative effort employed. If the gradient of the curve does not decrease after an initial period of rapid increase in total removals, then the population is not being reduced faster than its rate of replacement or at a rate high enough to achieve eradication. If this occurs, then alternative removal techniques need to be used. One problem with relying on the cumulative catch curve is that the curve will reach an asymptote despite not removing all individuals. This occurs when the residual population is no longer susceptible to the removal method (i.e. detectability p has been reduced to zero). Detecting this situation depends on the use of a monitoring protocol running in parallel with the primary removal method.

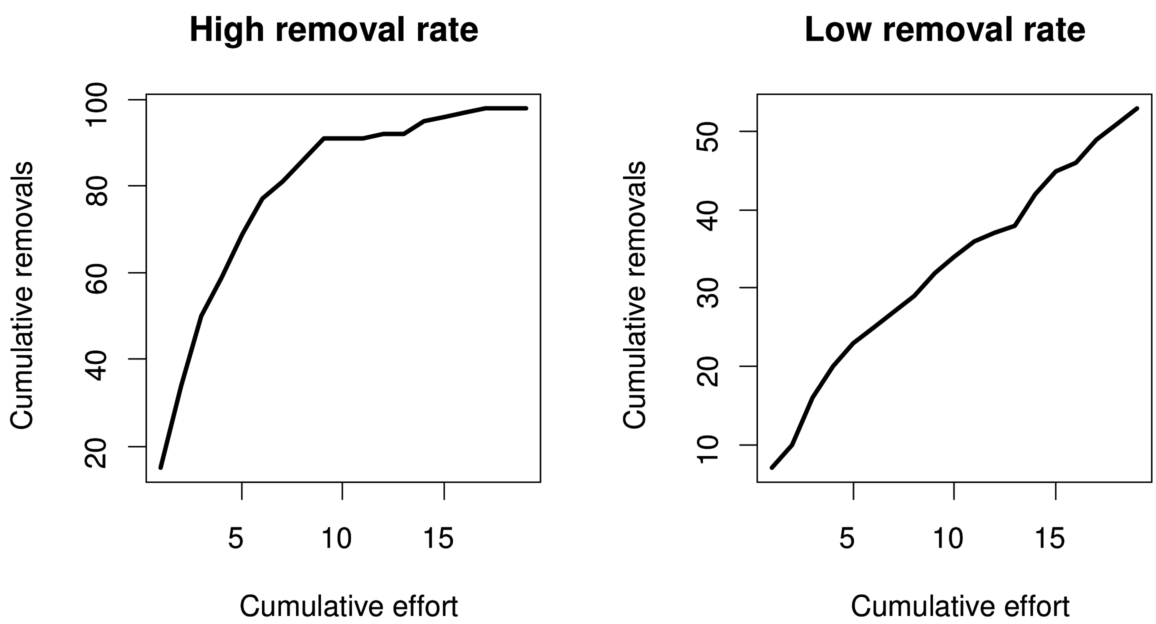

Figure 2. Plot of cumulative effort vs cumulative removals for a population of target animals with high and low removal rates. Eradication may not be feasible in the latter.

Indirect methods

Monitoring methods that produce data on the presence of one or more individuals, not of the individuals themselves (i.e. scats, footprints, etc.) are indirect monitoring methods. These are commonly referred to as 'indices of abundance'. An index is presumed to be some measure that is correlated with true abundance. Indices can be (a) presence–absence indices, or (b) relative abundance indices. Here we are primarily concerned with the ability of the index to detect the presence of a target species, especially during the final stages of the eradication program. Hence, the presence–absence index will be used extensively as part of this framework. In order to make reliable inferences using relative abundance indices, it is essential that they be calibrated against the population estimate used in (1) above. Hence it is essential that the data for both the population estimate (i.e. removal data) and the index data (e.g. scat counts) are collected simultaneously. The primary use of the index is to provide an alternative method of detection when the removal methods are no longer detecting individuals. If the index is able to detect the presence of individuals at low population densities, this information can then be used to determine the most likely remaining population size (Ramsey et al. 2011). Hence, indices can safeguard against a change in detection efficiency that could occur towards the end of the removal phase.

3 Pre-Implementation

The pre-implementation phase should be undertaken immediately prior to the implementation phase, or as nearly as possible beforehand. This is to ensure that baseline estimates of initial abundance do not change significantly before the start of the implementation phase.

3.1 Sampling frame

Before the pre-implementation monitoring can begin, the island needs to be divided into sampling units that cover the whole island and do not overlap. Sampling units can be regular or irregular sections of land (e.g., quadrats or transects). 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 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 island or survey region. In addition, these auxiliary variables can be used as stratification variables to increase the precision of abundance estimates.

3.2 Initial abundance estimate of target animals

An initial estimate of the size of the target 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 or resightings of marked individuals. The particular method chosen will depend on the ease with which the target species can be trapped and marked. A discussion of the most widely used methods and their advantages and disadvantages are given below and summarised in Table 1.

3.2.1 Abundance estimation based on complete counts

An estimate of abundance for the entire island can be based on a complete count of individuals within a sampling unit. It is assumed in a complete count that no animals are missed by sampling (i.e. perfect detectability). The estimate of abundance for the entire island is then calculated by adjusting the numbers counted for the fraction of the island area surveyed. While simple to calculate, the assumption of perfect detectability of individuals in sampling units rarely holds. In addition, even if possible, the complete enumeration of individuals in sampling units is usually expensive to obtain. Therefore most population estimation methods rely on an incomplete count, adjusted for the individuals missed (detectability).

3.2.2 Abundance estimation based on repeated counts

An estimate of the population size of the target population can be obtained by repeated counts of individuals collected from a random sample of sampling units (point counts) or by counting individuals along a transect (line transect methods). Individuals do not need to be physically marked but do need to be uniquely identified in some way on each sampling occasion at each sampling point. In the case of line transect sampling; at least two persons should record the locations of sighted individuals or record the perpendicular distance from the line of travel. Counts of animals can also be obtained by trapping or by passive methods such as automated cameras. Multiple sampling sessions are required at each sampling point to obtain sufficiently precise estimates.

3.2.3 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 involves physical capture. However, the risk with capture is that it may make individuals 'trap-shy', making their subsequent capture (and removal) less likely. Alternatively, individuals can be 'marked' in ways that do not require physical capture, such as through recognising distinctive markings on individuals or by genetic identification. If physical capture is used to mark individuals, it is advisable that individuals be sterilised using methods that will not affect their behaviour (i.e. methods that do not remove or destroy gonads or their function, e.g. tubal ligation for females and vasectomy for males). As a further precaution, GPS and/or radio telemetry collars can 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. If captured individuals are subject to sterilisation or fitted with radio telemetry devices, it is advisable to allow a period of recovery post-release so that normal behaviour can be resumed. A minimum of 14 days is adequate for most species.

3.2.4 Indirect counts (indices)

Indirect counts or 'indices' of individual signs (e.g. scats, footprints) usually cannot be used to estimate population abundance unless they are first calibrated (see above). However, index presence–absence data generated from replicated sampling of plots or sampling units can be used to estimate population abundance or density under certain assumptions. The idea is that the probability of occupancy of a site can be used to estimate abundance at that site by making use of the occupancy–abundance relationship (Royle & Nichols 2003). This method assumes that the main reason for the rate of detection of a species at a site is its abundance at that site. Hence, by modelling the structural relationship between species detection and abundance, it is possible to estimate population density or abundance for the region. However, there are a number of assumptions that need to be satisfied before the estimate can be interpreted in this way. Sampling must make use of an appropriate sampling frame (see above) and all individuals within a plot must be at risk of being detected. Hence, the estimates produced from this model are scale-specific and will vary with the size of the plot. It is also essential that there be no (or insignificant) movement of individuals between sampling units. Hence, sampling units must be independent and it therefore important that biological knowledge of the target species be incorporated into the design of surveys using this model. Further discussions around the design of surveys for this model can be found in Gopalaswamy et al. (2012) and Webb & Merrill (2012).

3.3 Spatial distribution

An important component of the pre-implementation monitoring is determining the spatial distribution of the target species. Information about spatial distribution is important for designing a monitoring program that can provide population estimates that are relatively unbiased and precise. If the target population is more or less 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 allocate strata.

3.4 Detection probability

The use of marking or GPS/radiotelemetry collars allows an estimation of the detection probability of different monitoring methods. If radio telemetry is used then trial monitoring can be targeted within the home range of each individual. At least 5–10 radio-collared individuals are required for these methods to be useful. A further use for radio-collared individuals is as 'Judas animals'; that is, they can be used to locate other animals that they interact with. However, this would only be useful for social species (e.g. ungulates).

Alternatively, individuals can be marked in a way that enables them to be subsequently identified during the course of the eradication program. The successive removal of marked individuals would provide additional information on the detectability of the removal techniques, as well on any additional monitoring methods. Ideally, 10–30 marked individuals should be released into the population, and these should be stratified by age, sex or spatial location, or a combination of these.

Baseline data collected during the pre-implementation phase can be used to optimise monitoring designs for the implementation phase. Data on population abundance, spatial distribution and detection probabilities of different monitoring techniques can all be used to design the optimal monitoring methods to use throughout the course of the eradication program, based on the availability and cost of different methods.

Table 1. Summary of methods used for estimation of population abundance.

Abundance measure	Description		Relative cost
Complete counts	Pros:	Easy to estimate Highly robust under unbiased selection of sampling units	High
	Cons:	Assumption of complete detection unrealistic except in limited circumstances	
Counts of unmarked animals	Pros:	Relatively robust under unbiased selection of sampling units Does not require animal capture (e.g. point counts)	Moderate
	Cons:	Requires identification of individuals Require repeat samples from each sampling unit to correct for detectability Relatively difficult to estimate Less precise than mark–recapture	
Mark–recapture	Pros:	Robust under unbiased selection of sampling units	Moderate/High
	Cons:	Requires individuals to be marked (or be identifiable) Requires adequate recaptures of marked individuals Relatively difficult to estimate	
Indirect counts	Pros:	Uses presence–absence data from index methods Wide variety of methods available Does not require capture or sighting of individuals	Low/Moderate
	Cons:	Fairly rigid assumptions required to avoid bias Not robust if there is significant movement of target animals between sampling units.	

4 Implementation

4.1 Data collection

The implementation phase involves a sequence of data collection as part of eradication efforts followed by synthesis of that data to update, in near real time, the estimate of the residual population remaining as well as the predicted removal effort required to achieve eradication.

Both 'conventional' data collection (using paper and pen) and digital data collection systems (consisting of field PCs with integrated databases) can be used to collect effort and removal data. However, given the intensive data requirements outlined by this framework, digital data collection is likely to be the more efficient method because it reduces the total amount of time spent collecting data, validates data entry in the field, and automates the synchronisation and analysis of data from multiple field staff simultaneously in the office. Using the RODBC library, R scripts can collate data from the majority of currently available databases and format it to meet the input requirements for this framework, creating a completely automated workflow from field data entry to data synthesis and model outputs.

4.2 Initial knockdown

In some eradication operations, especially if the initial abundance of the target species is high, it may be more efficient to attempt a broad scale initial knockdown of the population before attempting other removal methods. In most instances this initial knockdown is achieved either by primary or secondary poisoning following broad-scale aerial or ground-based baiting operations. In this situation it is possible to estimate population abundance prior to and after removal if the population is surveyed both immediately before and immediately after the removal and the number of removals is known. The estimator is known as the index-removal method (Skalski et al. 2005) and is relatively simple to calculate. However, it has relatively low precision unless a substantial proportion of individuals are removed. Its requirement of knowing the number removed by the knockdown operation may preclude its use in most circumstances. If the index-removal method cannot be used then the knockdown operation just essentially 'resets' the population to some lower abundance. In this instance the remainder of the framework can simply be implemented from this point. If possible, it would be advantageous to capture a number of individuals prior to the knockdown and release them (with identification marks or GPS/radio-telemetry collars) following the knockdown operation to allow estimates of detectability to be made for subsequent monitoring methods.

4.3 Primary removal method

Population estimates during implementation will be based largely on the removal rate achieved by the primary removal technique. For most of the eradication programs considered here, the primary removal technique will be either trapping or hunting, or a combination of the two. The data generated from the progressive removal of individuals can be used to estimate population abundance just prior to the start of removal activities as well as at various time points during eradication. For population estimates to be valid, two assumptions must be satisfied:

1. The population in the sampling region is closed (i.e. no births, deaths, immigration or emigration).
2. All individuals within the sampling region are at risk of being removed.

As a minimum, the following data should also be collected for each sampling region:

- number of individuals removed per unit time
- effort expended per unit time
- costs expended per unit time.

Hence, consideration needs to be given to a suitable time unit that should be used in the above accounting. This will normally be based around work schedules when considerable effort over the entire sampling region is being expended. Effort data will normally comprise either the number or density of traps, multiplied by the number of nights each trap was set (trap-nights). Alternatively, if hunting is used for removal, the effort data could comprise the total number of hours spent hunting or the total distance travelled while hunting.

4.4 Other monitoring methods

In addition to the primary removal method, other monitoring methods should also be used simultaneously during the eradication phase. These monitoring methods have two purposes:

Methods based on repeated counts at sampling units can be used to increase robustness of population estimates (e.g. automated camera traps) as they are able to correct counts for imperfect detection. This is especially useful if, for example, eradication is being undertaken only over a subset of strata on the island. In this case, additional monitoring will be required to estimate of the total population on the island accurately.

Indirect monitoring methods should also be implemented simultaneously with either the primary removal method or the methods based on repeated counts above. This enables the indirect index to be calibrated against the estimate of population abundance derived from these methods. Calibrated index methods can then be used towards the end of the eradication program to indicate the presence of individuals that may be missed by the primary removal methods.

4.5 Data synthesis

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 as well as predict the amount of effort required to achieve eradication. In the latter case, if removal costs are available, predicted effort should be cost-effective with respect to the probability of achieving eradication. Data from a minimum of three time units is usually required to generate an estimate of population abundance using removal data. The tasks undertaken during data synthesis will therefore include the following:

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

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 in the implementation phase. 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 alternative removal methods.

5 Decision support

The implementation phase, which includes data synthesis and feedback, continues until no more individuals are removed or detected and the residual population estimate is zero. At this point nominal eradication has been achieved. Monitoring then continues in order to confirm whether eradication has, in fact, been achieved (confirmation monitoring). At this stage eradication (E) has been either successful ($E = 1$) or not ($E = 0$). If survivors are detected, then eradication is known to have been unsuccessful ($E = 0$) and confirmation monitoring ceases until the remaining animals have been removed. The purpose of confirmation monitoring during this phase is to make an inference about the status of the eradication program (E) from data that returns *null* detections. Because monitoring methods have imperfect detection, we can never be certain that eradication has been achieved ($E = 1$). Therefore we must obtain a level of support for successful eradication by estimating the probability that eradication has been achieved $\Pr[E = 1]$. A question of interest at this stage is how much support should we have before we can declare successful eradication? Cessation of monitoring too soon risks falsely declaring eradication (type I error), whereas continuation of monitoring may waste resources if, in fact, the target species has already been eradicated (type II error).

5.1 Stopping rules

Two stopping rules can be used here for estimating the optimal amount of monitoring required to declare eradication success (e.g. Ramsey et al. 2009).

Stopping rule 1: Limit type I errors

This stopping rule aims to avoid falsely declaring eradication successful. This can be done by setting an agreed target for the type I error rate; for example, a 99% level of confidence that eradication was successful.

Stopping rule 2: Minimise the costs associated with both type I and II errors

This stopping rule uses an economic approach, first proposed by Regan et al. (2006) and modified by Ramsey et al. (2009), that calculates the net expected costs (NEC) of declaring eradication. The NEC is an estimate of the joint costs associated with both monitoring and the costs incurred if eradication is wrongly declared. Hence, the amount of monitoring that minimises the NEC is optimal with respect to minimising costs associated with both type I and II errors. Thus, the use of this stopping rule requires estimates of both the costs of monitoring (including monitoring after wrongly declaring eradication unsuccessful) and the costs of wrongly declaring eradication successful.

Once the stopping rule has been agreed on, the decision support stage will inform the most cost-effective mix of techniques during confirmation monitoring to achieve the stopping rule. Once confirmation monitoring has been completed and no further individuals have been detected, then eradication can be said to have been achieved.

5.2 Incorporating information collected into future eradications

For future eradication programs on the same or similar species, the data generated from previous eradication programs could be incorporated in the analysis as an estimate of the 'prior probability'. The prior probability is a subjective assessment of the likelihood that future eradication programs involving the same methods and species would achieve eradication. As more eradication programs are undertaken, the estimate of the prior probability gradually becomes more informative. Hence, as more eradication programs on similar species are undertaken, we are more informed about the risk that the techniques we use would fail to achieve eradication. This information can be used in the formal decision support analysis and updated after each new eradication program.

6 Summary of tasks undertaken at each stage of the framework

6.1 Pre-implementation

Objective: Estimate initial population abundance, distribution and detectability and use this information to design initial removal and monitoring strategies. If an initial knockdown operation is being undertaken (e.g. aerial baiting), then the tasks that follow should be undertaken immediately following the knockdown operation. Prior to any knockdown operation, individuals should be captured and placed in captivity, to be then marked and released following the completion of the knockdown operation. These individuals should be left to acclimatise for at least 14 days before the following tasks are undertaken.

Task 1: Initial population abundance

- **Sampling frames**
  - Considering the biology of the target species (i.e. home range size, movements and spatial distribution), divide the island up into sampling units that cover the whole island and do not overlap. Sampling units can be square (quadrats), rectangular (transects) or irregular sections. Do not combine different units (e.g. quadrats placed on transects) as this induces non-independence between the sampling units. Sampling units should be at least as large as the average home range size of the target species.
  - Select a sample of these units by drawing a random sample without replacement. The number of units sampled is usually some compromise between what is efficient statistically and what is feasible operationally. Restricted or stratified random sampling can be used where it is suspected that population abundance differs between zones on the island. In this case draw a random sample for each zone or strata separately.

- **Population estimate**
  - Conduct repeated sampling within each selected sampling unit. This will usually take the form of an incomplete count or a presence–absence survey that must be corrected for detectability.
  - *Point counts*: Detection using cameras is the preferred method because they are easy to deploy and are applicable for most of the usual vertebrate pest species, and repeated counts from cameras can be corrected for incomplete detectability. However, the number of unique individuals detected by each camera on each night has to be determined so this method is only useful for species that have distinct markings. Visual counts at each location are another method for obtaining point counts. Analysis of point count data can be undertaken using the binomial mixture model (BM model) (Royle 2004; Kéry et al. 2005). Place a camera within each randomly selected sampling unit at a desired location – lures can also be used – for a minimum of 10 nights. At each sampling unit record characteristics of the environment that may be used to model potential variation in animal density (i.e. habitat type, elevation, etc.).
  - *Transect counts*: As an alternative to point counts, animals can be counted along walked or flown transects. Two independent observers should be used each separately recording the location of individuals seen. By comparing the numbers of individuals seen by each observer and the numbers seen by both, the counts can be corrected for incomplete detectability (double count method) (Skalski et al. 2005).

- **Indices**
  - In concert with counts of individuals in sampling units, counts of animal signs or other indices of animal presence should also be undertaken within the same sampling units. These should also be undertaken for a minimum of 10 nights. Presence–absence data from these index monitoring surveys can also be used to estimate population abundance using the Royle–Nichols (RN) model (Royle & Nichols 2003). Signs should be removed following observation so they are not recounted during subsequent surveys.

Task 2: Detectability estimates

- **Detectability**
  - *Optional*: If a knockdown operation is used to obtain a large initial reduction in the population, then the capture tasks are done prior to the knockdown and the detectability tasks are performed using animals released following the knockdown and subsequent 14-day acclimatisaton period.
  - If animals are able to be trapped, set traps at either all selected sampling units or a subset of them, and mark any animals caught. If trapping is the primary removal method, the trapping technique or device should be different from that used as the primary removal method if possible. Marks should be able to be identified by other sampling methods (e.g. cameras or walked transects) and individuals should ideally also be radio-collared. A sample of 10–30 individuals of mixed sex and ages should be marked to enable estimates of detectability to be made for various monitoring or removal methods. However, the ease of obtaining this sample of marked individuals should be taken into account when implementing this task. If the initial population is small it may not be feasible or cost-effective to capture the minimum recommended number of animals. In this instance it is advisable to allocate a set amount of effort (and hence cost) to marking/collaring individuals, and if the required number is not obtained then this task should be abandoned.
  - Once the sample animals have been marked and released, preferably with radio-collars attached, some limited sampling using the primary removal technique should be undertaken to estimate initial detectability of that method. This should be undertaken within the home range or vicinity of marked individuals so that they are placed at-risk of capture. The proportion of marked individuals captured by the primary removal technique provides an estimate of the initial detectability. Recaptured animals can either be euthanised or released for later recapture. If released they will provide information on possible changes in detectability for subsequent capture events. However, they should be sterilized in case they cannot be recaptured.

Task 3: Optimal initial monitoring and removal designs

- **Initial monitoring design**
  - Population estimates derived from point counts or transect counts, as well as data collected from index methods, are used to design an initial monitoring program for each technique that will be used during the implementation phase. Simulation techniques can be used to determine the optimal number and distribution of sampling devices that result in maximising the precision of the estimate or index for a minimal sampling effort.
- **Initial removal design**
  - Estimates of the initial detectability of the removal technique and population abundance derived from count data, as well as data on the spatial distribution of the target population, are used to derive an optimal initial removal design. Simulation techniques can be used to determine the optimal amount and spatial distribution of devices that will result in all individuals being placed at risk of removal for a minimal effort.

6.2 Implementation

Objective: Conduct an eradication program by progressively removing individuals from the population using the primary removal technique. Conduct monitoring of the population in parallel using both direct count and index methods to detect possible changes in detectability of the primary removal method. At each time step, collect data on the individuals removed and effort and cost to remove them.

Update the population remaining at each time step, as well as the effort predicted to achieve eradication. Modify the program at each step to achieve the objective with minimal cost and effort.

Optional: If a knockdown operation was used to obtain a large initial reduction in the population, then this phase should be implemented as soon as possible following the knockdown operation.

While the population size > 0 for each time step, do the following:

Data collection

- **Task 1: Collect data from the primary removal technique**
  - Implement the initial removal design identified above, and record the number of individuals removed at each time step as well as the effort and cost to remove them.

- **Task 2: Conduct additional monitoring**
  - Conduct additional monitoring initially using the same sampling units as selected in the pre-implementation phase. Additional monitoring should include index methods (sign counts, cameras, or both) as a minimum.

Data synthesis

The following tasks require data collected from the *data collection* tasks given above. All data should be recorded on *pro forma* Excel spreadsheets or database tables designed specifically for each task and monitoring method. This data will then be processed and analysed using statistical and/or simulation models specifically designed to complete each task below. Outputs from each task will be collated and used to generate standard reports on the progress of the implementation phase. The analysis will be scripted in the statistical programming language R (R Development Core Team 2005) so that reports can be generated immediately following each removal session so that managers can implement changes to the program in near-real time. Examples of scripts for undertaking these analyses are provided as a set of supplementary digital files accompanying this report. Data format requirements for these R scripts are also provided in the supplementary materials.

- **Task 1: Update residual population abundance, index calibration and detection**
  - Use the data collected in Tasks 1 and 2 in 'Data collection' above to update the estimate of the residual population size. Calibrate index monitoring methods against population estimates at each time step. Calculate an updated estimate of detectability of the primary removal technique based on the removal rate, incorporating additional information from other monitoring data, including captures of marked individuals.

- **Task 2: Update removal design**
  - Based on the estimate of the residual population size and detectability for this time step, estimate the effort, cost and time required to eradicate the population. Use simulation techniques to optimise the effort required to achieve eradication for the minimal cost and time. Provide an updated removal design to the operations group for implementation.

- **Task 3: Update monitoring design**
  - Based on the estimate of the residual population size and its spatial distribution, update the monitoring design to optimise detection of the predicted residual population. Find the optimal mix of monitoring methods that maximise detection for minimal cost.
- **Task 4: Decide whether eradication is still feasible**
  - At each time step, plot the cumulative effort expended versus the cumulative catch per unit effort (e.g. Figure 2). For eradication to be feasible, the plot of cumulative catch versus cumulative CPUE should approach an asymptote, indicating the removal rate is high enough to consider eradication still feasible (Figure 2 — high removal rate). Note that an asymptotic cumulative catch curve does not guarantee that eradication is, or will be achieved. Alternatively, if the cumulative catch curve is a straight line or otherwise does not appear to reach an asymptote (Figure 2 — low removal rate), then eradication may not be feasible with the current strategy. Consideration must then be given to either radically changing the program (i.e. more effort, increased cost or different tools) or to terminate the program and implement an exit strategy.
- **Task 5: Decide whether nominal eradication has been achieved.**
  - Given that the program has proceeded to the point where eradication *appears* to have been achieved, a decision then needs to be made whether to enter the decision support phase. Once <u>all</u> monitoring sources fail to detect further individuals and the residual population estimate is equal to zero, then *nominal* eradication has been achieved. In practice, managers may wish to have several time steps where no further individuals are detected before declaring nominal eradication to allow extant individuals enough time to be detected and removed. Mop-up operations may also be implemented at this stage to target the removal of isolated individuals. Once nominal eradication has been achieved the program can move into the decision support phase, when monitoring to confirm eradication is undertaken.
  - <u>Caveat</u>: note that if the detectability of *all* monitoring tools decreases to zero, then it is possible that individuals may be extant but are, by definition, unable to be detected by any method. In this case the current program has failed and the most likely outcome is that eradication would be incorrectly declared a success. *Hence the use of multiple monitoring devices and methods is essential to maximise the likelihood that all individuals are ultimately detectable*.

6.3 Decision support

Objective: Once the program has achieved nominal eradication, undertake further monitoring to confirm eradication. Continue to monitor until a 'stopping rule' is reached.

As in the implementation phase, outputs from each task are collated and used to generate standard reports on the progress of the decision support phase, and are automated as much as possible so that reports can be generated in near-real-time so that managers can implement changes to the monitoring program as soon as possible.

- **Task 1: Decide on the appropriate stopping rule to be used to confirm eradication**
  - Stopping rule 1: Limit the type I error rate for falsely declaring eradication (e.g. 95% or 99% probability that eradication has been achieved, given confirmation monitoring fails to detect any individuals). Hence, the use of this stopping rule requires a decision on the error rate (e.g. 5% or 1% chance of falsely declaring eradication).
  - Stopping rule 2: Minimise the expected costs associated with both type I and II errors. This stopping rule requires an estimate of the cost of making a false declaration of eradication.

This cost could be estimated as the total cost of restarting the entire program from scratch. This stopping rule also requires per-unit costs of monitoring for each method used in confirmation monitoring.

- **Task 2: Estimate the optimal mix of monitoring techniques and effort required to confirm eradication (as per stopping rule used above)**
  - Based on estimates of detection probability and per-unit costs for each monitoring method, find the optimal mix of monitoring methods required to reach the stopping rule.
- **Task 3: If the stopping rule has been reached and no further individuals are detected, then eradication can be assumed to have been achieved.**
  - If individuals have been detected by confirmation monitoring then eradication has not yet been achieved and a return to the implementation phase to conduct mop-up operations is required. Mop-up operations will usually aim to remove localised individuals or groups.

6.4 Conclusion

The framework outlined above provides a general set of principles and actions that should be followed to maximise the information that is required to be able to make reliable decisions and inference regarding the progress and outcomes of an island eradication program on vertebrate pest species. Because it describes a framework, this document does not provide a recipe for undertaking all the tasks outlined. Instead it provides the principles and actions to be followed; it is up to the practitioner to devise the steps required to carry out each task.

It goes without saying that the ultimate success of the framework is highly dependent on the skills of the practitioners in completing the various tasks. In addition, tasks for the analysis and decision support aspects of the framework will require specifically designed scripts and components in order to complete each of these tasks and generate custom reports for the practitioners. The initial design of these specialist components are provided as part of this framework, and their use is illustrated in the case study in the next section. However day-to-day use of these components will require some specialist computing / data analysis skills in order for the completion of these tasks. Hence, it is essential that each eradication program team includes at least one specialist data analyst / programmer to provide this support.

7 Case study

This section sets out a case study that is worked through to show how the framework could be implemented on a real-world problem. The case study involves the collection of data and analysis for an eradication program conducted on a simulated island pest population. For the purposes of the case study the pest population consists of simulated cats on the island of San Nicolas, as the recently completed eradication program there provides a relevant context for evaluating the framework.

7.1 Structure of the simulated data

The pest population of cats on the island all had a home range defined as bivariate Gaussian, drawn from a distribution with a mean 95% area of 1.2 km^2, equal to the mean home range size of cats on nearby islands. Home ranges of cats were fixed for the duration of the simulated eradication program, and the catchability of cats varied from high to low. The true size of this population was 100 cats and their home range centres were randomly distributed on the island (Figure 3).

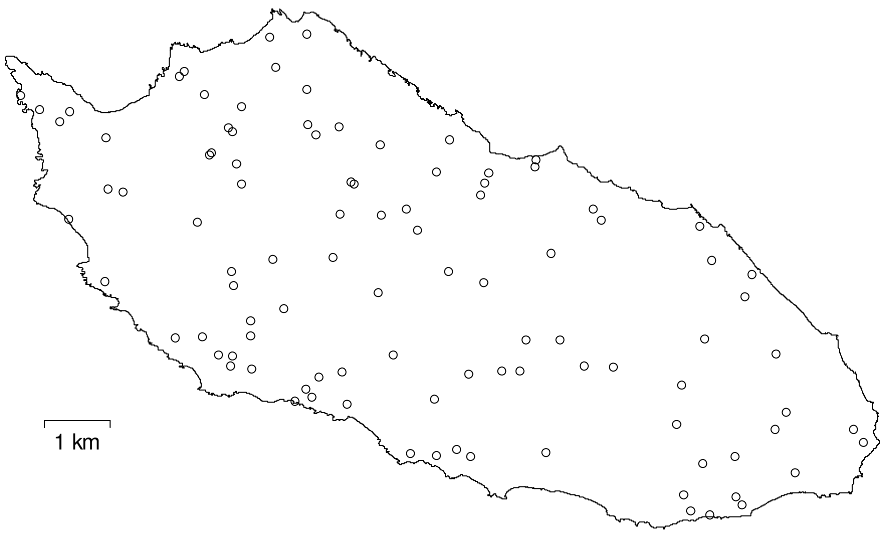

Figure 3. Simulated cat population inhabiting San Nicolas Island prior to the start of the eradication program. Circles depict the locations of cat home range centres. The true population size is equal to 100.

7.2 Simulated eradication program

Eradication of the cats was by trapping and removal. Simulated trapping sessions were conducted each month using various numbers of randomly placed traps. A cat had a possibility of being caught if a trap happened to be placed within its home range. However, the actual probability of being captured depended on the distance between the cat's home range centre and the trap, as well as its catchability value according to the function

$$p = g0\, e^{\left(\frac{-d^2}{2\sigma^2}\right)}$$ [Equation 2]

Where d is the distance between the trap and home range centre, $g0$ is the per-night catchability when the trap and home range centre locations coincide (i.e. $d = 0$) and σ is proportional to the home range size of the cat. The algorithm of Ramsey et al. (2005), which simulates captures in traps using a competing Poisson process, was used to simulate removal trapping.

7.3 Simulated monitoring

Additional monitoring of the cat population occurred directly following each removal session. Two forms of monitoring were used: cameras and sign surveys. Detection of cats by cameras depended only on where the device was placed in relation to the cat's home range, so it was not affected by varying catchability of cats. In all other respects, the algorithm used to simulate camera monitoring was the same as that used for removal trapping.

Sign surveys occurred at plots placed randomly on a simulated road network on the island. As for cameras, detection in sign surveys depended only on the location of the plot in relation to the cat's home range.

7.4 Structure of the case study

Using the simulated population of cats, the case study followed the steps outlined in the framework. To simplify the complexity of the simulations, some of the decision-making steps in the framework were simplified. These relate primarily to tasks involving designing 'optimal' monitoring and removal designs in terms of the number of devices to use. Here we simplify these tasks by assuming set maximum numbers of monitoring and trapping devices are available to be used at each time point. Data synthesis and decision support then determine the optimal number of repeat surveys.

7.5 Pre-implementation

Task 1: Initial population abundance

Sampling frame: Based on prior knowledge of the home range size of cats from other islands in the region (around 1–2 km^2) (Guttilla 2007), the island was divided into square plots, each 1 km^2 (Figure 4). These were used as the basis for conducting population estimates. In this case study we assumed that 30 cameras were available for monitoring. Hence, for the pre-implementation monitoring, 30 plots were selected at random, with each plot containing one camera for 20 nights.

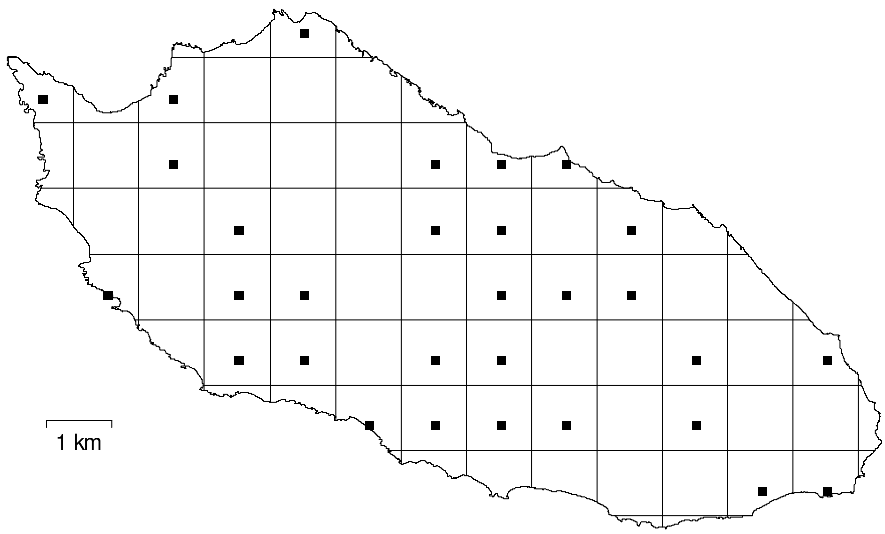

Figure 4. Sampling frame for the island, consisting of square plots, each 1 km^2, and the locations of 30 randomly selected plots containing cameras (small closed squares) used to estimate population size in the pre-implementation section.

Population estimate: The resulting camera data generated from 20 nights sampling using the camera locations in Figure 4 is provided as a CSV file in the supplementary digital files. If individual cats are identifiable, then the data are the number of unique individuals seen per camera per night. These type of data comprise point counts and can be analysed with the binomial mixture (BM) model. Otherwise, the data consist only of an index of the number of photos of cats per camera per night, and can be reduced to presence–absence data and analysed with the Royle–Nichols model. The assumptions for the latter are that the sampling points are independent and there is no (or little) movement of cats between sampling units. In addition, with both methods there is an assumption that all cats inhabiting a plot are at risk of being detected by the camera. Hence, it is important that plot size be about equal to the average home range size for the resulting estimates to be valid. Even in this case the resulting estimates should be treated as approximate.

Bayesian statistical methods were used to fit both of these models to the camera data contained in the supplementary files coded in the freely available software `OpenBUGS` (Thomas et al. 2006). Both methods produce estimates with 95% credible intervals that overlap the true abundance of 100 (Table 2). The BM model is relatively unbiased, which is a consequence of knowing the number of individual cats seen by each camera. However, the precision of the estimate is relatively poor, a consequence of the relatively small sample size. The RN model also performs reasonably well, given that it uses only the presence–absence data rather than the count of individuals. The `OpenBUGS` code for carrying out these analyses is reproduced in the Appendix.

Detectability: In addition to the initial population estimates, some limited trapping was undertaken to place a unique mark on 10 cats distributed randomly on the island. These cats were then released back into the population and their subsequent recapture rate used as a guide to the success of the removal trapping during the implementation phase. Cats selected to be 'marked' were randomly selected from the population.

Table 2. Pre-implementation population estimates from 30 cameras set for 20 nights using the binomial-mixture model (BM) that assumes the counts are of unique individuals and the Royle–Nichols model (RN) that records the same data as just presence-absence. SE – standard error; LCL – Lower 95% credible interval; UCL – upper 95% credible interval.

Model	Estimate	SE	LCL	UCL
BM	99.1	53.1	49.2	198.5
RN	90.0	21.7	54.7	138.9

7.6 Implementation

Removal trapping

The removal of cats was undertaken exclusively by trap and removal using leg-hold type traps with a maximum of 200 traps available to be used for the removal program. The removal program was undertaken using simulated trapping occurring at 'monthly' intervals (trapping sessions). During each session, traps were set for 10 consecutive nights and trap placement was re-randomized each session. The actual trapping effort varied between 100-200 traps set each session, which was undertaken to represent variability in effort due to sprung traps or other factors that might lead to differences in trapping effort each session. The data collected each session consisted of the number of individual cats removed, the number of marked cats removed and the total number of trap-nights.

Additional monitoring

Immediately following each removal trapping session, additional monitoring was then performed using cameras and sign surveys. A total of 25-30 cameras were deployed at random locations and set for 10 nights as well as 40-60 sign survey plots set on a simulated road network also set for 10 nights (Figure 5). The actual number of cameras and sign stations set each month varied between these limits. This was undertaken to represent variability in effort due to things like camera failure or weather events. Each month the location of cameras and sign stations (on roads) were placed at different random locations.

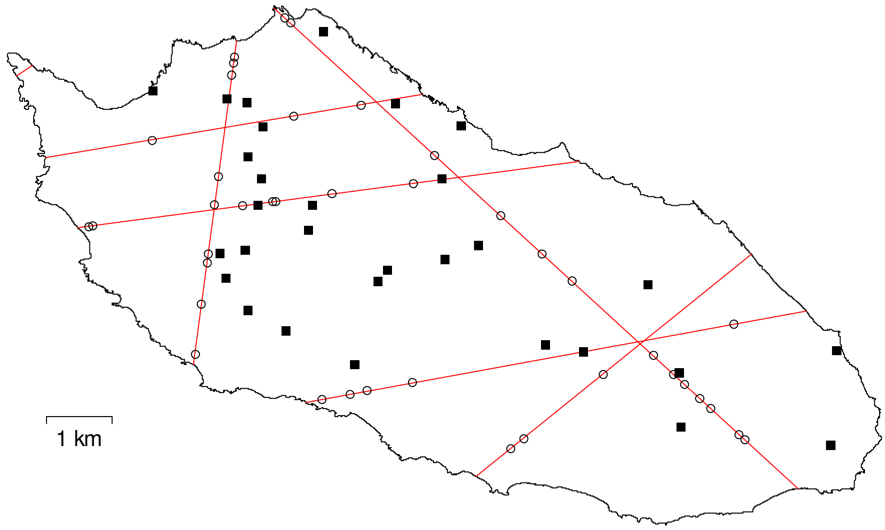

Figure 5. Additional monitoring undertaken in conjunction with removal trapping. Lines are the simulated 'road' network with 40 randomly placed sign stations (open circles). Squares show locations of 30 randomly placed cameras. Both cameras and sign station locations were re-randomised each month.

Data collection – Data synthesis steps

The removal program was instigated at the beginning of month 1. A data synthesis step was performed after four months of removal trapping, and again after each subsequent month. The following section shows the results from selected data synthesis updates for a single run of the simulation model.

Data synthesis, month 4

The data collected following four months of removal trapping, and additional monitoring data, is given in Table 3. The plot of cumulative removals versus cumulative effort (Figure 6) shows little sign of reaching a plateau, indicating that the trapping rate has yet to show much evidence of a decline. In summary, 79 cats were removed, of which 8 had been previously marked and released. Hence, two marked cats remained uncaptured. In the first month, 18 cameras and 24 sign stations detected at least one cat.

Task 1: Update residual population abundance

This data synthesis task consisted of estimating the most likely size of the remaining population using the data in Table 3. A composite model that combined a removal estimator (Zippin 1958) with models for the camera and sign data that employed a Royle–Nichols type model were used to analyse the data. The Royle–Nichols model's abundance component was linked with the removal estimator abundance component, so that detections by any of the alternative monitoring methods, as well as captures in traps, all contributed to the estimate of population abundance in the model. The `OpenBUGS` code for running the composite model is given in the Appendix.

Table 3. Summary of data collected at month 4 of the removal program.

Month	Cats removed	Marked cats	Camera hits	Sign station hits
1	33	1	18	24
2	23	1	13	16
3	14	5	6	11
4	9	1	5	11

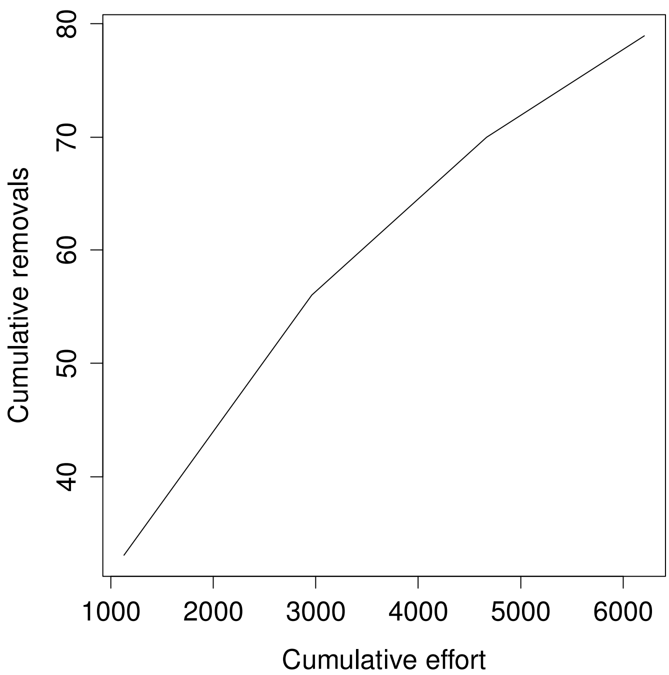

Figure 6. Plot of cumulative trapping effort vs cumulative removals following four months of removal effort.

Estimates of the remaining population was made using the composite model, as well as a plain removal type model (e.g. Zippin 1958) that did not use the data from the additional monitoring (Table 4). Based on these estimates, the best estimates of the remaining cat population were 21 (composite) and 25 (removal). However, note the much poorer precision of the removal estimate, which predicts the remaining population to lie between 4 and 70 with 95% confidence. This is a consequence of the small sample size (four data points).

Table 4. Estimates of the remaining population size on the island following four months of removal trapping using two estimators — 'composite' (combining removal data and additional monitoring data) and 'removal' (using removal data only). The actual number of cats remaining was 21. LCL – lower 95% credible interval; UCL – upper 95% credible interval.

Model	Estimate	LCL	UCL
Composite	21	7	40
Removal	25	4	70

Task 2: Update removal design

The second task used the estimates of detectability for the removal trapping and the estimated residual population size to estimate the amount (and cost) of removal effort likely to be required to eradicate the residual population. Here we will focus on estimates of the amount of removal trapping effort required to eradicate the residual population. This can be visualised by a plot of the relationship between the residual population in the next trapping session and the trapping effort in that session (Figure 7). This relationship was estimated from the parameters for trap detectability and residual population size from the composite model. From the plot we can see that employing the same amount of effort in the next session (200 traps) is likely to reduce the population from the current size of 21 cats to around 9 cats. Employing 500 traps set for 10 nights is likely to reduce it to around 3 cats. However, the large variation in these estimates, which vary between a possible zero and 21 cats removed, indicate a high degree of uncertainty about the actual likelihood of future removals. This is a consequence of the relatively small number of removal sessions undertaken so far and the resulting imprecision of the estimated detection parameters.

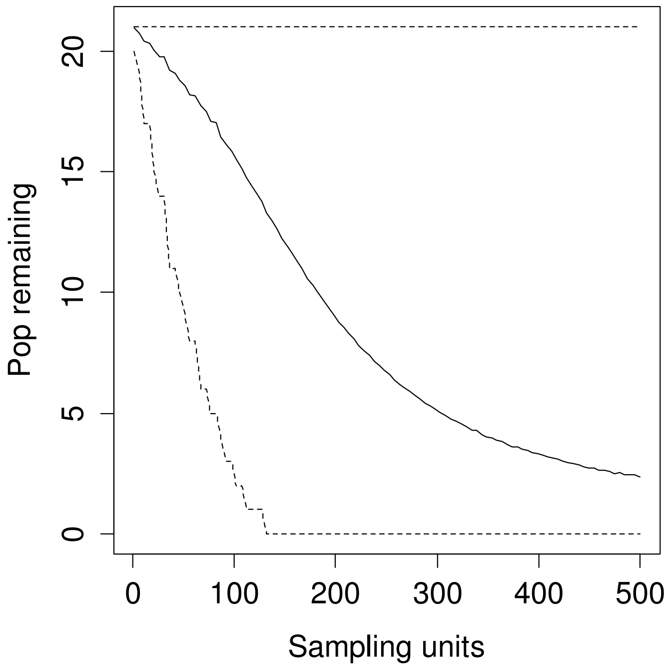

Figure 7. Estimate of the relationship between trapping effort (number of traps set for 10 nights) and the residual population size in the next trapping session following four trapping sessions. Dashed lines are 95% credible intervals.

Task 3: Update monitoring design

In addition to estimates of the likely effort required to remove the remaining individuals, we can also estimate the relationship between numbers of cameras and sign survey plots and probability of detection (monitoring sensitivity). This information could be used to design more sensitive monitoring strategies with these devices in order to maximise detection rates. The relationship between sensitivity (probability of detection) and numbers of sampling units is given in Figure 8, using the estimates of detectability for both cameras and sign surveys derived from the composite model. Probabilities of detection, given the current sample sizes, are around 0.15 and 0.25 per session for cameras and sign surveys respectively.

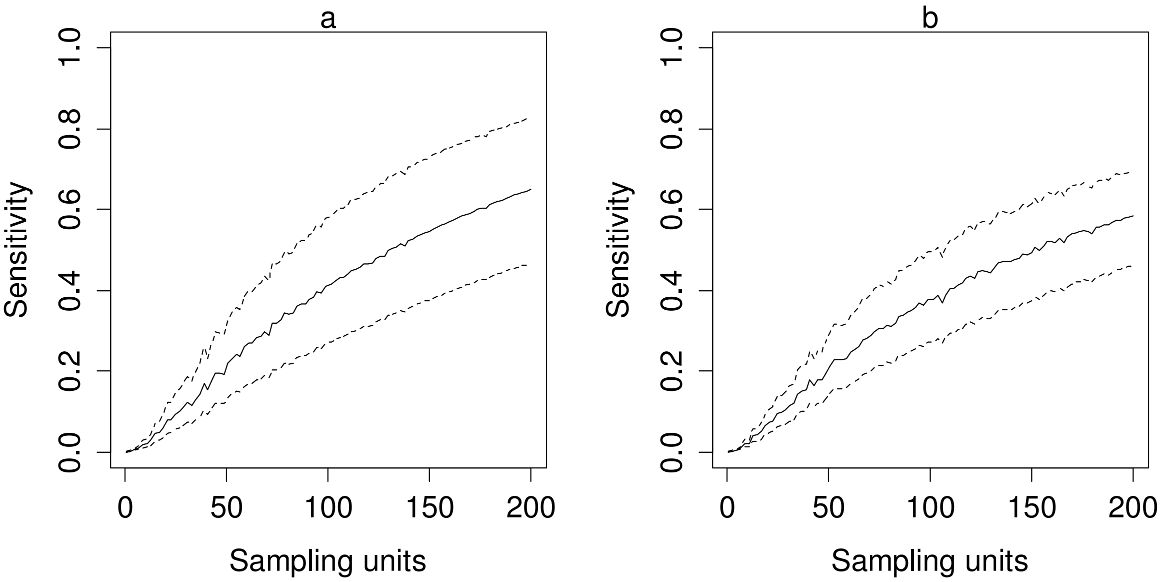

Figure 8. Estimates of the relationship between the number of sampling units for (a) cameras and (b) sign survey plots and the sensitivity (probability of detection) following four trapping sessions.

Task 5: Decide whether nominal eradication has been achieved

As the estimate of the residual population size indicates many cats were still likely to be present, additional removal steps were required.

Data synthesis, month 9

Because cats were detected in each of months 5–8 by removal trapping and additional monitoring, we will skip the results for these months to avoid repetition, and proceed to month 9 where no cats were detected in the removal trapping or camera sampling but were detected on the sign stations (Table 5). The total number of cats removed was now 90.

After nine months the plot of cumulative effort versus cumulative removals (Figure 9) had started to plateau, indicating that the trapping program had been effective at reducing the population of cats and that the catch rate is declining. We could conclude from this that eradication was likely to be feasible with the current removal strategy.

Table 5. Summary of data collected by the end of month 9 of the removal program. Numbers in brackets are cumulative removals.

Month	cats removed	marked cats	camera hits	sign station hits
1	33 (33)	1 (1)	18	24
2	23 (56)	1 (2)	13	16
3	14 (70)	5 (7)	6	11
4	9 (79)	1 (8)	5	11
5	3 (82)	0 (8)	5	7
6	4 (86)	0 (8)	2	2
7	3 (89)	1 (9)	0	5
8	1 (90)	0 (9)	1	3
9	0 (90)	0 (9)	0	2

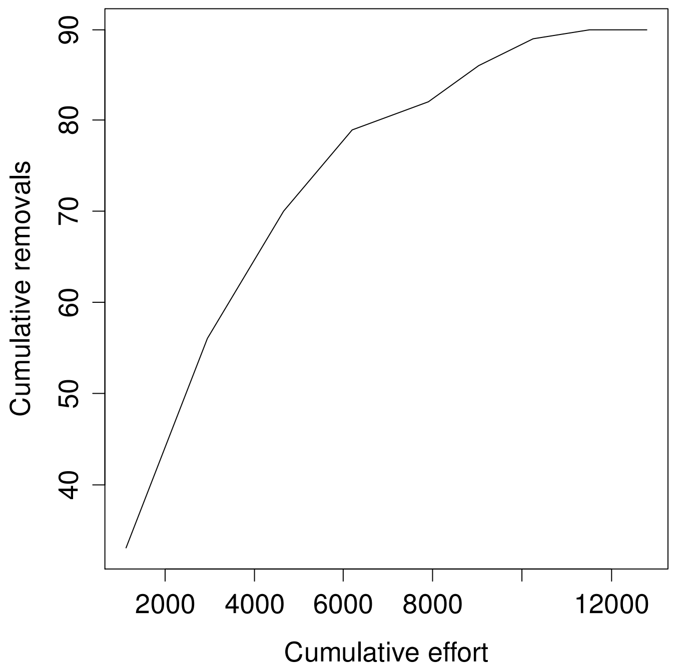

Figure 9. Plot of cumulative trapping effort vs cumulative removals following nine months of removal effort.

Task 1: Update residual population size

The estimate of the remaining population from our two models (Table 6) indicated a best estimate of 4 (composite) and 1 (removal) cats remaining. The actual number of cats remaining was 10. Updating the models with additional data thus resulted in a slightly worse estimate of the correct number of remaining cats compared with the results after four months.

Table 6. Estimates of the remaining population size on the island following nine months of removal trapping using two estimators: 'composite' (combining removal data and additional monitoring data) and 'removal' (using removal data only). The actual number of cats remaining is 10. *LCL* – lower 95% credible interval; *UCL* – upper 95% credible interval.

Model	Estimate	LCL	UCL
Composite	4	1	7
Removal	1	0	5

Task 2: Update removal design

The likely effort required to reduce the remaining population from the current estimate of 4 cats to zero cats was estimated to be around 500 traps set for 10 nights (Figure 10). The current trapping effort of 200 traps set for 10 nights was likely to reduce the population to 1 cat. However, this estimate was highly uncertain (Figure 10).

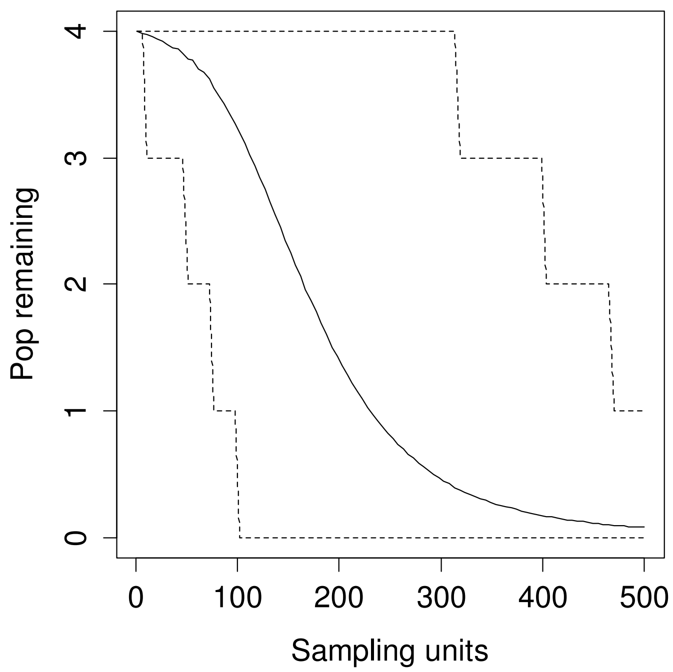

Figure 10. Estimate of the relationship between trapping effort (number of traps set for 10 nights) and the residual population size in the next trapping session following 9 trapping sessions. Dashed lines are 95% credible intervals.

Task 3: Update monitoring design

Updated estimates of the sensitivity of cameras and sign surveys for detecting cats are given in Figure 11. The precision of estimates had improved compared with those following four trapping sessions (see Figure 8).

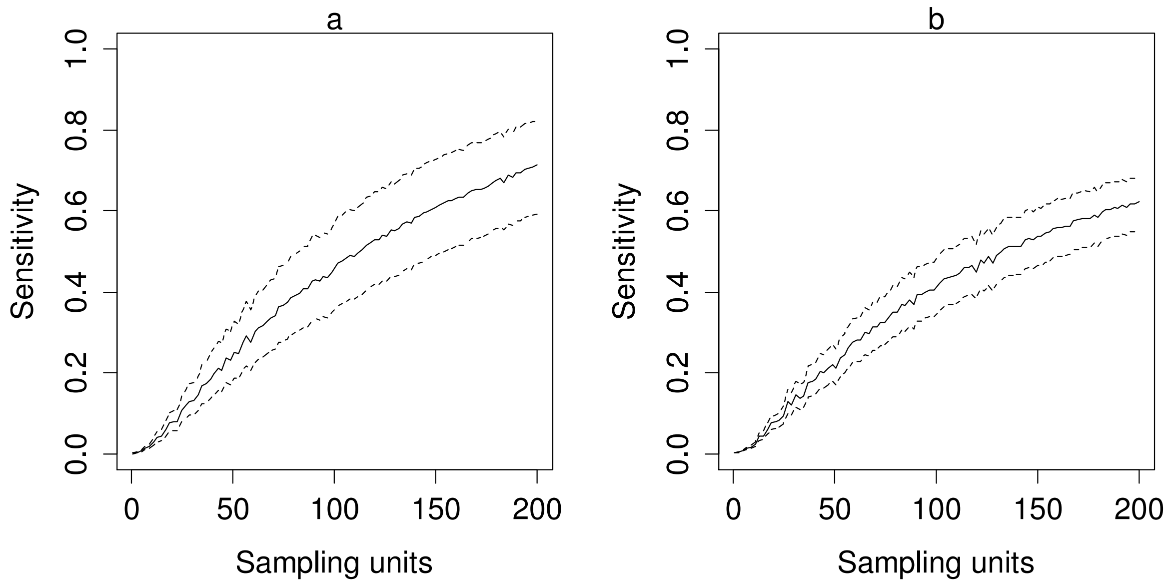

Figure 11. Estimates of the relationship between the number of sampling units for (a) cameras and (b) sign survey plots and the sensitivity (probability of detection) following trapping sessions.

Task 5: Decide whether nominal eradication has been achieved

Since both models indicated the presence of remaining cats, and we knew that that one marked cat was also still extant, a decision was made to continue the implementation phase.

Data synthesis, month 17

Again to avoid repetition, we will skip to the results of month 17 when no cats were detected by removal trapping, cameras or sign surveys. The last marked cat had been removed during month 15 (Table 7). The total number of cats removed was now 99, so there was one hard-to-detect cat still remaining on the island.

After 17 months the plot of cumulative effort versus cumulative removals showed a slight upward trend from about 10 000 trap-nights. This indicates that the removal program was continuing to remove cats but at a much lower rate, and that the removal program was able to remove some of the more hard-to-detect cats (Figure 12). The estimate of the remaining population from our two models (Table 8) indicated a best estimate of 0 (composite) and 0 (removal) cats remaining. The actual number of cats remaining was 1.

Table 7. Summary of data collected by the end of month 17 of the removal program. Numbers in brackets are cumulative removals.

Month	cats removed	marked cats	camera hits	sign station hits
1	33 (33)	1 (1)	18	24
2	23 (56)	1 (2)	13	16
3	14 (70)	5 (7)	6	11
4	9 (79)	1 (8)	5	11
5	3 (82)	0 (8)	5	7
6	4 (86)	0 (8)	2	2
7	3 (89)	1 (9)	0	5
8	1 (90)	0 (9)	1	3
9	0 (90)	0 (9)	0	2
10	2 (92)	0 (9)	0	5
11	2 (94)	0 (9)	0	0
12	0 (94)	0 (9)	1	1
13	0 (94)	0 (9)	1	2
14	1 (95)	0 (9)	2	5
15	3 (98)	1 (10)	0	2
16	1 (99)	0 (10)	0	1
17	0 (99)	0 (10)	0	0

Task 5: Decide whether nominal eradication has been achieved

The decision about whether nominal eradication has been achieved is based on the estimate of the remaining population from the composite model. This estimate was now zero. Hence, based on the information collected to date from trapping, two forms of additional monitoring and the status of the marked segment of the population, we declared that cats had been nominally eradicated and moved to the decision support phase for confirmation. At this point, there was actually one cat remaining on the island.

Note that while in this example the estimate of the remaining population was zero cats following the first instance when no cats were detected by any method, this will not necessarily be the case generally. Depending on the data from prior months, the estimator may require several ‘all clear’ results before an estimate of zero cats remaining is obtained. For example, Table 9 contains data from an additional simulation run of the model containing trapping and monitoring data from 19 sessions. In this particular instance, it happened that all cats were eradicated by month 15. However, the composite model required three ‘all clear’ results before it indicated nominal eradication was achieved (Table 10).

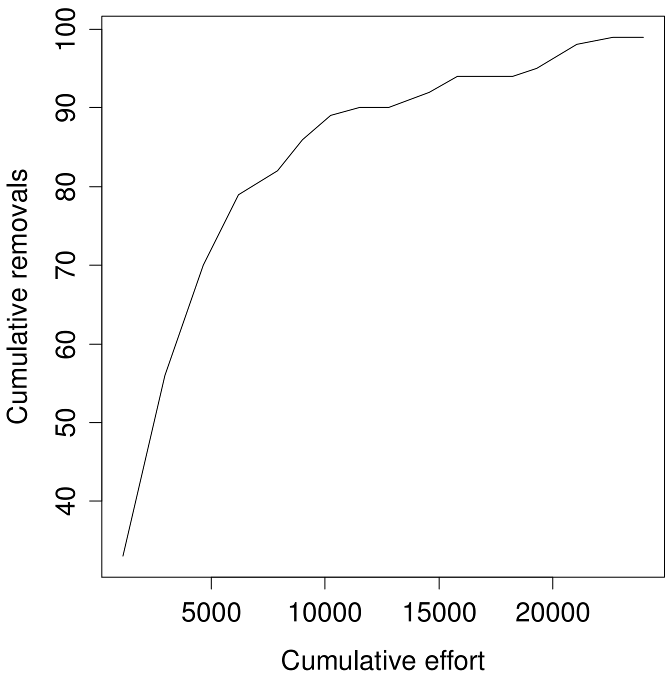

Figure 12. Plot of cumulative trapping effort vs cumulative removals following 17 months of removal effort.

Table 8. Estimates of the remaining population size on the island following 17 months of removal trapping using two estimators: 'composite' (combining removal data and additional monitoring data) and 'removal' (using removal data only). The actual number of cats remaining is 1. *LCL* – lower 95% credible interval; *UCL* – upper 95% credible interval.

Model	Estimate	LCL	UCL
Composite	0	0	1
Removal	0	0	2

Table 9. Summary of data collected for an additional run of the model, illustrating the need for several 'all clear' results before nominal eradication could be declared (Table 10). Cats were actually eradicated in month 15. Numbers in brackets are the cumulative removals.

Month	cats removed	marked cats	camera hits	sign station hits
1	45 (45)	6 (6)	6	20
2	16 (61)	1 (7)	8	12
3	16 (77)	1 (8)	5	16
4	3 (80)	0 (8)	5	5
5	6 (86)	1 (9)	2	9
6	1 (87)	0 (9)	5	13
7	1 (88)	0 (9)	7	5
8	2 (90)	0 (9)	5	3
9	1 (91)	0 (9)	2	8
10	3 (94)	0 (9)	1	5
11	1 (95)	0 (9)	0	4
12	0 (95)	0 (9)	1	5
13	1 (96)	0 (9)	2	4
14	2 (98)	0 (9)	0	1
15	2 (100)	1 (10)	0	0
16	0 (100)	0 (10)	0	0
17	0 (100)	0 (10)	0	0
18	0 (100)	0 (10)	0	0
19	0 (100)	0 (10)	0	0

Table 10. Composite model estimates of the remaining population size on the island after months 16–19 for the data given in Table 9. Nominal eradication was declared after month 18 following three 'all clear' results. The actual number of cats remaining following month 15 was 0.

Month	Estimate	LCL	UCL
16	2	0	5
17	1	0	3
18	0	0	2
19	0	0	1

7.7 Decision support

The objective of the decision support phase is to undertake further monitoring to 'confirm' that eradication has been achieved.

Task 1: Decide an appropriate stopping rule

In this case study we decided that eradication would be judged to have been achieved when monitoring indicated that the probability of falsely declaring eradication successful was less than 1%.

Task 2: Estimate the mix of monitoring techniques and effort required to confirm eradication.

Revised estimates of detectability of cameras and sign surveys were updated with every data synthesis step from the composite model during the implementation phase. These estimates were used to determine the optimal amount of effort in terms of the number of repeat surveys using a set amount of monitoring devices. A total of 30 cameras were available, so we elected to use all of these. In addition, it was also possible to set and check at least 200 sign stations in one day. We elected to deploy cameras and sign surveys over 10 consecutive nights, so we needed to determine how many repeat surveys (total effort) were required to reach our stopping rule.

The probability of detecting a cat using 30 cameras and between 0 and 200 sign stations set on the road network is given in Figure 13a. The probability of detecting at least one cat given 30 cameras and 200 sign stations was 0.76 (95% CL: 0.69–0.82). Hence, in order to reach our stopping rule (1% chance of false eradication), we needed to undertake at least five repeat surveys of the island using 30 cameras and 200 sign stations, randomly reallocated to plots before each survey (Figure 13b).

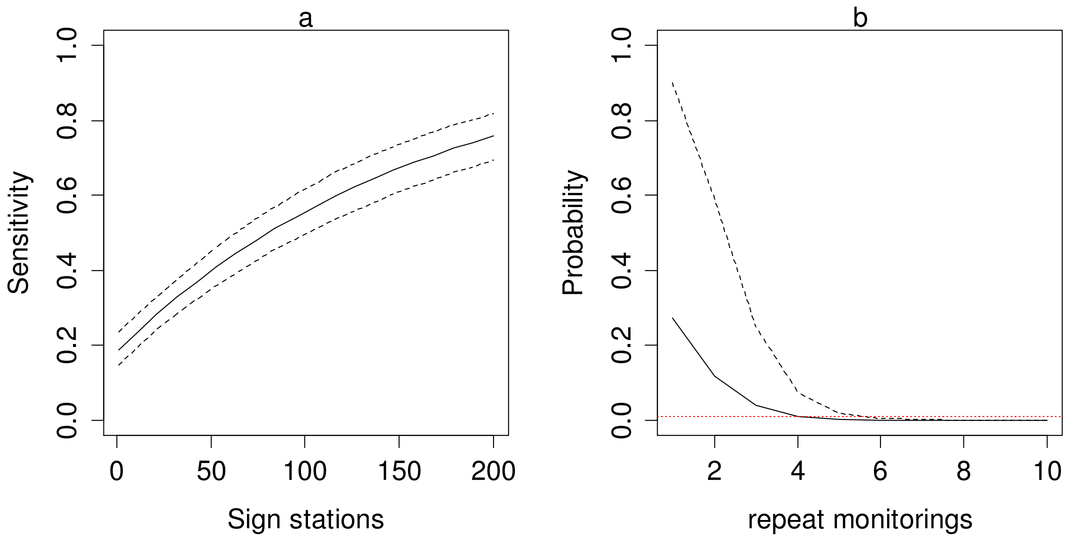

Figure 13. (a) The probability of detecting at lease one cat using monitoring with 30 cameras and up to 200 sign stations set for 10 nights, and (b) the probability of falsely declaring successful eradication for between 1 and 10 repeat surveys using 30 cameras and 200 sign stations. Our stopping rule (< 1%) was triggered after five repeat surveys. Dashed lines are 95% credible intervals.

Confirmation monitoring results

After initiating the recommended monitoring protocol above, both a camera and sign stations detected cat presence after the first survey. Hence, the last cat on the island was detected and the locations of the sign and camera detections used to direct mop-up operations. The recommended monitoring protocol was then repeated, and no cats were detected. Hence, the stopping rule was triggered and the eradication program was declared a success.

Since all the simulated cats were detected using the protocols outlined above, the case study illustrates a correctly classified eradication. However, this is just for a single simulated population and a single run of the model. A more accurate estimate of the utility of the framework can be estimated by estimating the percentage of correctly classified eradications from multiple runs of the model. This was undertaken as follows.

7.8 Power of the framework to correctly classify eradication success

To determine the utility of the decision rules used in the case study to correctly classify eradication as successful, we ran simulations of four similar scenarios, with 500 replicates for each. For each simulated 'eradication program' a new simulated cat population (again of size 100) was generated, and implementation, data synthesis and decision support phases were then undertaken. Populations that were successfully eradicated following the decision support phase were deemed successful; while those that still had cats remaining were deemed to have failed. In all cases, our nominal probability of 'eradication failure' set during decision support was set to 1%. Hence, out of 500 simulated runs of the framework, we would expect no more than 5 of these to fail, given our stopping rule of 1%.

Simulation structure

For each simulated eradication program we generated a population of 100 'cats' distributed at random over the island. Each individual cat in the population had catchability values (i.e. g0, σ in Equation 2) drawn from a distribution (Figure 14). This ensured that cats varied in their ability to be trapped (i.e. varying g0). However, their detection in other 'passive' monitoring methods (cameras, sign surveys) depended only on their home range overlap with these devices (i.e. σ).

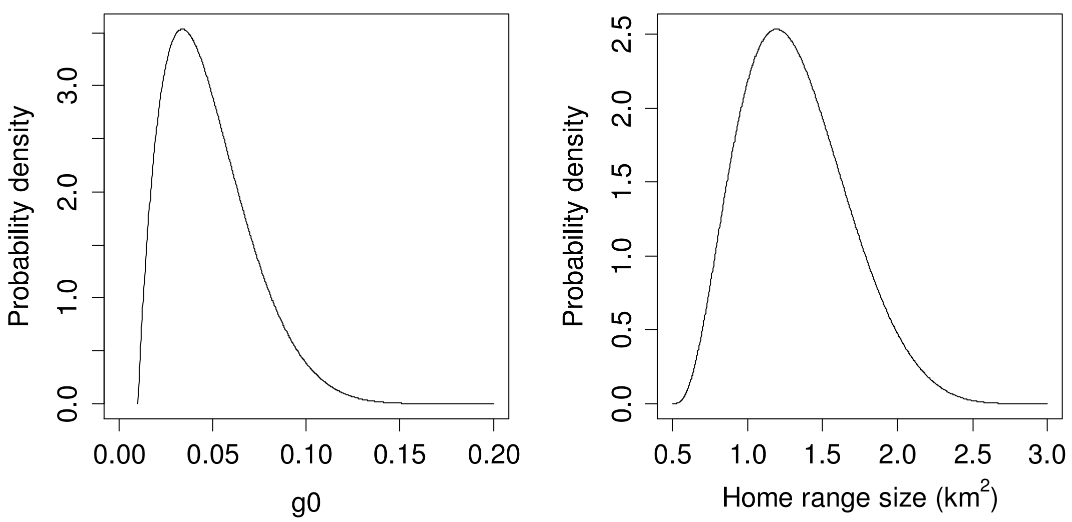

Figure 14. Distribution of 'catchability' of cats in traps in terms of the two parameters of the detection function (equation 2), *g*0 (daily catchability at home range centre) and *σ* (home range size).

For each population we undertook the eradication framework as outlined in the preceding case study. That is, 'monthly' removal trapping sessions conducted with leg-hold traps supplemented by monitoring with cameras and sign survey plots. Data synthesis was conducted following month 3, and consisted of an estimate of the residual population size using the composite model. This was repeated following each subsequent month's trapping and monitoring until the residual population estimate reached zero (nominal eradication).

The decision support phase was then implemented using estimates of detectability for cameras and sign surveys derived from the composite model, using the data collected up to that point. The optimal number of repeat surveys required to reach the stopping rule (1% in these simulations) using cameras and sign surveys was then estimated for a set number of units for each method. The set number of surveys was then undertaken on the residual population (which may or may not have been zero). If at least one cat was detected by any method, then that cat was removed and the entire set number of surveys was repeated. This continued while cats were detected. Once the set number of surveys was completed and no cats were detected, then eradication was declared successful. If the residual population size at that point was also zero, then that eradication program was correctly classified as a success. However, if the residual population size was greater than zero, then the eradication program was incorrectly classified (i.e. eradication declared successful when it had actually failed). The power of the eradication framework was then calculated as the proportion of 500 simulated eradication programs that correctly classified successful eradication.

We conducted several different runs of the framework to examine the effects of varying the mix of monitoring methods and numbers of units in the decision support phase (i.e. numbers of cameras and sign surveys used in each survey). In addition, we also varied the amount of removal trapping effort used in each session during the implementation phase. This was undertaken to determine whether greater effort during the implementation phase as opposed to the decision support phase or vice versa had the greatest influence on the power of the eradication framework. Four scenarios in total were evaluated (Table 11), with 500 replicate eradication programs undertaken under each scenario.

Table 11. Summary of the four scenarios evaluated to estimate the effects of varying sampling effort on the power to achieve successful eradication using the framework.

	Implementation Phase			Decision support phase	
Scenario	**Traps**	**Cameras**	**Sign plots**	**Cameras**	**Sign plots**
1	200	30	100	30	200
2	200	30	100	60	0
3	300	30	100	30	200
4	300	30	100	60	0

Results of the power analysis

A summary of the results from 500 replicate runs of the framework under each scenario is given in Table 12. In scenarios 1 and 2, an average of 19 trapping sessions was required to achieve nominal eradication (i.e. a prediction of zero cats remaining from the composite model). In scenarios 3 and 4 the number of trapping sessions averaged 13, a reflection of the increased trapping effort used for these scenarios. In all cases the average number of cats that actually remained following the implementation phase was less than 1.

Following the decision support phase, the actual probability of eradication failure was higher than the nominal level (1%) for both scenarios 1 and 3 when monitoring was undertaken with both cameras and sign surveys. However, when monitoring during decision support was undertaken with cameras only, the probability of eradication failure was less than the nominal level (1%). The reason for the higher failure rate for scenarios 1 and 3 is the slight bias caused by the non-random placement of sign survey plots across the island, as they were placed on roads. This is a drawback of such ‘convenience sampling’ in that placing sampling units on a road network induces non-independence between the sampling units. Thus, each sign survey plot does not independently contribute to the detection process, and resulting estimates of the sensitivity of sign surveys will be biased upwards. This means estimates of the sampling effort required to confirm eradication using sign surveys will be biased downwards, and more sampling effort than estimated is actually required. Hence, managers should bear this in mind when inferring the power of monitoring programs that uses such non-independent sampling. However, even with the biased nature of sign surveys, the influence of this on the probability of eradication failure was still less than 10% for scenario 1 (Table 12).

Table 12. Results of the power analysis for each of the four scenarios examined. Values are the mean from 500 replicate runs of the framework. Sessions – average number of trapping sessions taken to achieve nominal eradication; Residual N – average number of cats actually remaining following the declaration of nominal eradication. Monitor effort – number of repeat monitors required to reach the stopping rule during decision support (i.e. 1% chance or less of eradication failure); P – actual probability of eradication failure.

Implementation phase			Decision support phase	
Scenario	**Sessions**	**Residual N**	**Monitor effort**	**P**
1	19	0.94	8	0.07
2	19	0.95	18	0.002
3	13	0.65	9	0.04
4	13	0.65	23	0.00

As a further evaluation method, we examined the total cost of the framework for each scenario using cost values for each method using estimates derived from the recent cat eradication program on San Nicolas island (Ramsey et al. 2011) (Table 13). The total costs included the cost of the removal trapping, calculated as the number of trap nights used in each session multiplied by the number of sessions required to reach nominal eradication. Implementation costs did not include the costs of additional monitoring, as these were constant among the four scenarios. Costs of the decision support phase included the cost of camera nights multiplied by the number of repeat surveys required to reach the stopping rule. For sign surveys the cost was calculated as the cost to walk the entire road network (37.5 km) multiplied by the number of repeat surveys. These costs were then multiplied by the number of times the decision support phase needed to be repeated if a cat was detected.

Table 13. Cost of different monitoring techniques per unit of effort.

Method		
Trapping	**Sign survey**	**Camera**
$3.0/trap-night	$76.2/km	$1.7/trap-night

The scenarios with the least cost were scenarios 2 and 4, chiefly because they did not involve sign surveys. Sign surveys were generally expensive and did not contribute as much to the sensitivity of decision support monitoring, compared to cameras. However, this should not be taken as a recommendation not to undertake sign surveys, as the cost of 100 sign survey plots would be the same as 200 or 300 sign survey plots if the entire road network had to be traversed, no matter how many plots were set. Hence, sign surveys become more cost-effective the more that are undertaken. During the implementation phase it appeared that the extra cost per session associated with increasing the numbers of removal traps in scenarios 3 and 4 was mostly offset by a reduced number of sessions required to reach nominal eradication (Table 14).

Table 14. The costs associated with undertaking the framework for each scenario. Values are the mean costs ($1000s) over 500 replicate simulations using the monitoring costs per unit in Table 13.

Implementation		Decision support		
Scenario	**Trapping**	**Cameras**	**Sign surveys**	**Total cost**
1	114.2	7.4	41.4	162.9
2	116.4	36.8	0.0	153.3
3	116.3	7.5	41.9	165.7
4	119.5	38.6	0.0	158.1

8 Conclusions

The case study illustrates the practical use of the framework and the steps required to be undertaken during each phase. While we have tried to provide a scenario that is as comprehensive as possible, several factors were simplified. For example, one aspect of the data collected during the pre-implementation and implementation phases is the spatial distribution of detections. The use of this data was largely ignored in the case study as it is difficult to apply a general-purpose adaptive decision about its use. However, in real applications of the framework, spatial data can be valuable for informing the future distribution of trapping and monitoring effort, and it is of vital importance during the final stages of the implementation phase when efficiency gains can be made by targeting certain areas.

Because of time constraints only a limited number of simulated scenarios were examined to test the adequacy of the framework for correctly predicting eradication success. Further work in this area is warranted, especially for examining the effects of learned avoidance behaviour by the residual population, non-random population distributions and habitat stratification, as well as incorporating a richer set of adaptive decisions (e.g. using spatial information). We recommend conducting further work in this area using baseline information from eradication programs conducted on a range of taxa (e.g. ungulates, rodents). We believe some valuable extensions to the framework could be made as a result.

Accompanying this framework is a set of standard quantitative analysis tools provided as scripts coded in the R statistical language, which were written to conduct the analysis contained in this report. They are therefore fairly 'vanilla' and intended to cope with the basic framework and decision-making process as outlined in the case study. Hence, they will almost certainly require some modification before they can be applied to a particular situation. A set of calling scripts are also provided, written in the lightweight markup language `Markdown` (`R Markdown`). These scripts read data, conduct analyses and produce output as a self-contained HTML file that can be viewed in any web browser. These files and a simple set of instructions are available in the zip file accompanying this document.

Although the framework outlined in this report may not be comprehensive and therefore suitable for every island eradication program, we believe the framework does provide a more structured decision-making process and strategy that can be followed logically. It also provides a basic set of quantitative tools to aid managers in the decision-making process. Ultimately, the framework provides a toolset that managers can, and should, adapt for their particular eradication scenario. We believe that adopting a framework such as the one presented here will result in more efficient, informed and cost-effective eradication programs for insular populations of vertebrate pest species.

References

Bomford, M. & O'Brien, P. (1995) Eradication or control for vertebrate pests? *Wildlife Society Bulletin*, **23**, 249–255.

Borchers, D.L., Buckland, S.T. & Zucchini, W. (2010) *Estimating Animal Abundance: Closed Populations*. Springer Science, Berlin.

Gopalaswamy, A.M., Karanth, K.U., Kumar, N.S. & Macdonald, D.W. (2012) Estimating tropical forest ungulate densities from sign surveys using abundance models of occupancy. *Animal Conservation* (in press).

Guttilla, D.A. (2007) *Effects of Sterilization on Movement, Home Range Behaviour, and Habitat Use of Feral Cats on Santa Catalina Island, California.* MSc thesis, California State University, Fullerton.

Kéry, M., Royle, J.A. & Schmid, H. (2005) Modeling avian abundance from replicated counts using binomial mixture models. *Ecological Applications*, **15**, 1450–1461.

Myers, J.H., Simberloff, D., Kuris, A.M. & Carey, J.R. (2000) Eradication revisited: dealing with exotic species. *Trends in Ecology & Evolution*, **15**, 316–320.

R Development Core Team. (2005) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna.

Ramsey, D., Efford, M., 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.S.L., Parkes, J.P., Will, D., Hanson, C.C. & Campbell, K.J. (2011) Quantifying the Success of Feral Cat Eradication, San Nicolas Island, California. *New Zealand Journal of Ecology*, **35**, 163–173.

Regan, T.J., McCarthy, M.A., Baxter, P.W.J., Panetta, F.D. & Possingham, H.P. (2006) Optimal eradication: when to stop looking for an invasive plant. *Ecology Letters*, **9**, 759–766.

Royle, J.A. (2004) Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation*, **27**, 375–386.

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

Simberloff, D. & Rejmanek, M. (eds) (2011) *Encyclopedia of Biological Invasions*, 1st edition. University of California Press.

Skalski, J.R., Ryding, K.E. & Millspaugh, J. (2005) *Wildlife Demography: Analysis of Sex, Age, and Count Data*, 1st edition. Academic Press.

Thomas, A., O'Hara, R., Ligges, U. & Sturtz, S. (2006) *Making BUGS Open*.

Webb, N.F. & Merrill, E.H. (2012) Simulating carnivore movements: An occupancy–abundance relationship for surveying wolves. *Wildlife Society Bulletin*, **36**, 240–247.

Williams, B.K., Nichols, J.D. & Conroy, M.J. (2002) *Analysis and Management of Animal Populations*. Academic Press, San Diego.

Zippin, C. (1958) The removal method of population estimation. *Journal of Wildlife Management*, **22**, 82–90.

APPENDIX 1

OpenBUGS models developed as part of the framework

Analysis of point counts using the BM model (count of unique individuals per sampling unit per night)

```
model{

      for(i in 1:M){
      # Population abundance
      N[i] ~ dpois(lambda[i])
      log(lambda[i])<- b
      }
# Detection
      for(i in 1:n) {
      C[i] ~ dbin(p[i], N[site[i]])
      logit(p[i])<- a
      }

      a ~ dnorm(0,0.01)I(-20,20)
      b ~ dnorm(0,0.01)I(-20,20)

      TotalN<- sum(N[])
      PopEst<- exp(b)*nq
}
```

Royle–Nichols occupancy–abundance model (abundance estimate from index presence–absence data)

```
model{

	for(i in 1:M){
	# Abundance
	N[i] ~ dpois(lambda[i])
	log(lambda[i])<- b
	mu[i] <- 1-pow(1-r[i],N[i])
	logit(r[i])<- a

	Y[i] ~ dbin(mu[i],J)
	}
	a ~ dnorm(0,0.01)I(-20,20)
	b ~ dnorm(0,0.01)I(-20,20)

	TotalN<- sum(N[])
	PopEst<- exp(b)*nq
}
```

'Composite' model (removal + Royle–Nichols models) for combining removal and index data.

```
model {
      for(i in 1:K) {
      n[i] ~ dbin(p1[i], N[i]) # removal trapping
      cams[i] ~ dbin(p2[i],ncams[i]) # cameras
      sign[i] ~ dbin(p3[i],nsign[i]) # sign
      N[i+1] <- N[i] - n[i]
      p2[i] <- 1-pow(1-r2[i],N[i])
      p3[i] <- 1-pow(1-r3[i],N[i])

      logit(p1[i])<- a1 + b1*ntraps[i]
      logit(r2[i])<- a2
      logit(r3[i])<- a3

      }

      # prior on initial population size N[1]
      N[1] <- round(exp(u))
      nsum<- log(sum(n[]))
      u ~ dunif(nsum,PopMax)
      a1 ~ dunif(-20,10)
      a2 ~ dunif(-20,10)
      a3 ~ dunif(-20,10)
      b1 ~ dunif(-10,10)

      Nresid<- N[1] - sum(n[]) # Population remaining
}
```

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