

Methods for estimating probability of species eradication using integrated surveillance

September 2025

Giorgia Vattiato, Andrew M Gormley

Bioeconomy Science Institute Maiangi Taiao

Contract Report registration number: 2526-0132

Prepared for: Department of Conservation

© Department of Conservation 2026

This report has been produced by the New Zealand Institute for Bioeconomy Science Ltd for the New Zealand Department of Conservation. All copyright in this report is the property of the Crown and any unauthorised publication, reproduction, or adaptation of this report is a breach of that copyright and illegal.

Crown copyright ©. This copyright work is licensed under the Creative Commons Attribution 4.0 International licence. In essence, you are free to copy, distribute and adapt the work, as long as you attribute the work to the Department of Conservation and abide by the other licence terms. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>. Please note that the Department of Conservation's logo may not be used in any way which infringes any provision of the Flags, Emblems, and Names Protection Act 1981 or would infringe such provision if the relevant use occurred within New Zealand. Attribution to the Department of Conservation should be in written form and not by reproduction of any logo.

Reviewed by:

Simon Howard
Quantitative Wildlife Ecologist
Bioeconomy Science Institute

Approved for release by:

Duane Peltzer
Portfolio Leader – Managing Invasive Species
Bioeconomy Science Institute

Contents

Summary.....	iv
1 Introduction	1
2 Existing statistical approaches to estimating the probability of species eradication.....	2
2.1 Occupancy modelling	3
2.2 Proof of Absence model	5
2.3 Random walk model.....	9
3 General considerations	10
3.1 Bayesian extensions	10
3.2 Estimates of detection	11
3.3 Emerging detection methods: eDNA and acoustic detection	12
4 Integrating different detection probabilities across frameworks.....	13
4.1 Why integration is needed	13
5 Model performance at very low population densities	14
5.1 Theoretical challenges	14
5.2 Impact on different models	15
6 Conclusions.....	16
7 References.....	18
 Appendix 1 – Experimental design for estimate detection parameters.....	 23

Summary

Project and client

This project was carried out for the Department of Conservation as part of the PF2050 knowledge and innovation research projects.

Objectives

The project objectives were to:

- complete a literature review that summarises statistical approaches for integrated surveillance
- produce the experimental design for a field programme to estimate detection parameters for a range of surveillance devices and methods under standardised conditions.

Summary

This report summarised three modelling strategies for estimating the probability of species eradication

- **Occupancy Modelling (OM):** This framework divides a study area into grid cells and estimates the probability of occupancy and the probability of detection. While widely used for monitoring purposes and estimating species distribution, it may struggle to estimate detection probabilities accurately when populations are near zero.
- **Proof of Absence (PoA) Framework:** Designed specifically for proving a successful eradication, this approach models detection as a continuous function of distance from a device. It is considered robust for irregular landscapes where animal movement is non-uniform. However, reliable estimates of the key parameters may not be available for all species-habitat combinations, nor when populations are at very low densities and individuals may have non-stable home ranges.
- **Random Walk Models:** These are individual-based simulations that model the physical paths of animals across a virtual landscape. While highly realistic, they are computationally intensive and more importantly require detailed data on animal movement and habitat selection that are typically unavailable for low-density populations, and very difficult to estimate.

1 Introduction

Effective eradication of an invasive species depends not only on the removal of all individuals, but also on the ability to detect any survivors or re-invaders with high confidence (Bomford & O'Brien 1995). As eradication efforts scale up across complex landscapes, a critical challenge is understanding how to optimally deploy detection tools – both existing and emerging – to ensure that claims of successful eradication are robust (i.e. species are not falsely declared absent).

At very low densities, detection can become difficult because there are very few individuals potentially spread over a large area. Furthermore, individuals that remain after partial control may not be representative of the original population (Spiegel et al. 2017). Behavioural traits of surviving animals, such as neophobia, trap-shyness, risk-aversion (Vattiato et al. 2021; Johnstone, Price, Garvey 2024; Johnstone, Garvey, Hickling 2024), may make detection even more difficult. Sparse detection networks are attractive from an operational perspective, but risk survivors occupying small home ranges and living in surveillance 'gaps'. These factors mean that it is quite possible to undertake surveillance and not detect any animals, even though survivors remain *in situ*.

This variability in detectability must be explicitly acknowledged as an assumption in any model that attempts to estimate the probability of eradication. Furthermore, differences in individual behaviour of the last remaining animals mean that it is unlikely that any single detection method will provide sufficient sensitivity on its own. Instead, integrated surveillance strategies combining multiple detection tools offer the best chance of detecting rare individuals and supporting robust declarations of eradication success.

There are many approaches for monitoring wildlife populations, the choice of which will depend greatly on the intended purpose. Here we are not concerned with general monitoring of populations for the purpose of assessing trends, but rather monitoring and surveillance for the purpose of confirming the success (or otherwise) of eradicating invasive species. The context of this report is the estimation of the probability that a species has been eradicated.

After intensive control has been carried out, the hope is that the species will either be entirely absent while the monitoring is being carried out, or, if the species is present, only very few individuals remain. Surveillance in eradication programmes will therefore often result in non-detections; obviously this will always be the case if the species has truly been eradicated. However, non-detection does not necessarily mean that a species is truly absent: individuals may remain undetected despite being present due to there being very low numbers. Managers are therefore faced with a decision about the amount of 'negative surveillance' (i.e. non-detections) required in order to declare a successful eradication.

To formalise this uncertainty, statistical models can be used to quantify the probability that a species is truly absent given the surveillance. The resulting probability depends on the intensity of surveillance (i.e. how hard we looked), which in turn is shaped by device-specific detection probabilities, the number and spatial distribution of devices, and the duration of surveillance. These detection probabilities will vary by species, as well as other factors such as habitat and season.

A range of statistical approaches have been developed to estimate the probability of species eradication from non-detection data following eradication attempts. These methods typically use detection histories to infer whether a population persists, with early frameworks assuming fixed and known detection probabilities ($p_{\text{detection}}$). However, subsequent work has emphasised the importance of explicitly modelling uncertainty in detection (Ramsey et al. 2005; Ramsey et al. 2011; Rout et al. 2009). As a result, hierarchical models, Bayesian frameworks, and occupancy models are now widely used to incorporate this uncertainty, allowing managers to estimate how

much additional effort is needed to reach a desired level of confidence in species absence. This is particularly important when populations are near zero, meaning that false negatives become more likely and confidence in absence is harder to obtain. Accurately estimating detection probabilities under these conditions requires a careful understanding of the strengths and limitations of each detection tool, including static methods such as camera traps and audio recorders, mobile methods such as detection dogs, and emerging technologies such as eDNA. The ability to integrate information across these diverse sources in a statistically rigorous way is essential for effective decision making.

In this report we summarise statistical approaches used to date for estimating the probability of species eradication and integrating data from multiple surveillance methods. The review is structured in three parts: (i) a description and comparison of current approaches to estimating probability of eradication and modelling detection uncertainty; (ii) a synthesis of methods for integrating multiple sources of detection data; and (iii) an exploration of how model performance is affected as population density approaches zero. The ultimate goal is to support more effective, scalable, and cost-efficient eradication strategies by improving our ability to detect low-density populations and formally incorporate multiple data sources into eradication declarations.

2 Existing statistical approaches to estimating the probability of species eradication

Methods for estimating probability of species eradication have been developed to address the fact that animals can be present but not detected. Modelling how often animals might be missed gives managers more confidence about whether a species is truly absent from an area. Fundamental to this process is the estimation of the probability of detection of an individual animal (conditional on the individual being present in the specified area over the period of surveillance) from a single detection device and/or detection method, and scaling up across repeated sessions and surveillance points.

There are three principal ways the probability of detection is applied to estimating the probability of eradication. First, the probability of detection can be quantified at the level of grid cells or sites, treating detection as a binary outcome for each of these sampling units, given that an individual is present in the grid cell during the surveillance period. This approach is fundamental to occupancy modelling (OM; section 2.1), and can also be used in the proof of absence model (PoA; section 2.2). Second, the g_0 - σ framework models the detection process in continuous space, in which the baseline detectability (g_0) declines with distance from a device or surveillance point according to its movement scale (σ). This approach forms the basis of the PoA model (section 2.2). The third approach is used by 'random walk' models (section 2.3), whereby movement paths of individual animals are simulated, and the models then estimate the probability of encountering a detection device and the probability of interacting with it given that encounter.

The following sections describe the main statistical approaches used to estimate the probability of species eradication, outlining their assumptions, applications, and limitations. We focus our assessment on the following three modelling approaches: occupancy, proof of absence, and random walk models.

2.1 Occupancy modelling

2.1.1 Overview

Occupancy modelling (OM) has been widely used in conservation biology and biodiversity monitoring (MacKenzie et al. 2006). OM approaches are typically used for estimating species distribution, monitoring population trends in cases when abundance cannot be estimated, and determining associations with habitat. In these cases, the population is generally not at very low levels. In New Zealand it has informed management decisions for invasive species and threatened native fauna. For example, MacKenzie et al. (2002) applied it to estimate the distribution of introduced predators, while Garrard et al. (2008) and Guillera-Aroita et al. (2014) adapted occupancy models to address detection biases in structured and incidental survey data. Occupancy modelling is used to analyse the information from the Department of Conservation's Tier 1 biodiversity monitoring and reporting system (BMRS) for estimating the distribution of bird species across public conservation land.

Occupancy modelling is a statistical framework that is used to estimate the proportion of 'sites' in a study area that are occupied by a species of interest (MacKenzie et al. 2002). It is commonly used in cases where actual abundance is impossible (or impractical) to quantify. For most species there is no natural definition of a 'site', and therefore a grid-cell method is applied whereby the study area is subdivided into discrete spatial units of an appropriate size, typically square cells. Detection is treated as a binary event within each grid cell: an animal is either detected or not during survey effort in that cell.

In the OM framework, repeat surveys are carried out in each grid cell, which allows for two key parameters to be estimated simultaneously: the probability that a species occupies a grid cell (ψ), and the probability of detecting the species given it is present in a grid cell (p). Surveys are carried out across grid cells (all or a subset of grid cells), the results of which are either 'detection' or 'non-detection' events. Non-detection in a grid cell does not necessarily imply absence at that location – it may be due to imperfect detection even though the grid cell is occupied. The repeated surveys allow estimation of detection probabilities separate from occupancy.

The repeated surveys at each grid cell are conducted over a short time period, during which occupancy is assumed to remain constant (the closure assumption). The repeat surveys generate a detection history for each grid cell. For example, a detection history for a grid cell of 101 would indicate the species was detected on first and third visits but not the second, whereas a detection history of 000 would indicate the species was not detected at all in that grid cell.

The likelihood of each detection history is then modelled as a function of occupancy probability ψ and detection probability p . Each observed detection pattern can arise in different ways depending on whether the grid cell is truly occupied or not. For example, for the detection history 101, the probability of this history is given by $\psi \times p^2 \times (1 - p)$; that is, occupies the grid cell, and is detected on two occasions and not detected on one occasion. If the species is never detected across multiple visits (e.g. 000), this could mean the species is either truly absent from the grid cell ($1 - \psi$), or present but was missed on each of the three surveys, resulting in $(1 - \psi) + \psi(1 - p)^3$.

Occupancy models quantify the likelihood of observing each detection history under both scenarios, then estimate ψ and p by finding the values that make the observed data most likely (maximum likelihood estimation), or treat ψ and p as random variables and use Bayesian estimation to combine prior information with the surveillance data to estimate posterior distributions of the model parameters (see MacKenzie et al. 2006 for statistical model details).

Spatially explicit covariates, such as habitat type, elevation, and resource distribution, can be incorporated into OM to improve occupancy estimates across grid cells. These habitat-based models generate predictive surfaces that highlight areas with elevated likelihood of species presence, allowing survey effort to be allocated more strategically (Guillera-Arroita 2017). By focusing surveys in high-probability zones, eradication managers can potentially resolve uncertainty about species presence, especially where detection probabilities are low.

By modelling occupancy probabilities across all grid cells, OM provides grid-cell-specific estimates of the probability that the species is present. Where this estimated occupancy probability is very low – especially after many surveys with no detections – researchers can conclude with greater confidence that the species is absent.

2.1.2 Limitations of occupancy models for probability of species eradication

Occupancy modelling is an established method to address ecological questions related to species distributions. It has recently been proposed to be a tool to estimate the probability of species eradication given no detections (MacKenzie & Bertoia 2024). The model is intuitively appealing because it quantifies the probability of occupancy (i.e. presence) across a grid-cell system. When those probabilities are uniformly low, confidence in eradication success increases. However, the robust quantitative methods for scaling up the ψ and p values from individual grid cells to an eradication landscape have not yet been formally described. This raises questions about the generality of the model, which can currently only be addressed through speculation.

A key assumption of standard occupancy models is site closure; that is, the occupancy status of each site remains constant over the survey period. However, this assumption is often unrealistic, particularly for mobile or seasonal species, whose presence at a site may vary in response to resource availability, breeding cycles, or weather. For instance, a site might appear unoccupied during some visits but be used intermittently by transient individuals, violating the closure assumption and introducing bias into occupancy estimates (Kéry & Royle 2016). This issue becomes especially pronounced when survey periods span biologically meaningful timescales during which movement patterns are dynamic.

OM can use data collected during the knockdown phase of an eradication programme to estimate the ψ and p parameters. However, p is defined as the probability of detecting at least one of an unspecified number of individuals, and it is obviously easier to detect one of many individuals than it is to detect a lone individual. Therefore, because p is estimated when the density of the population is relatively high, it is unclear how the detection probabilities will relate to state after knockdown when the population is near zero. This raises concerns about the generalisation of p to when no detections are made. As a result, even multiple surveys without detections may lead to incorrect inferences about whether the species is absent or not (Guillera et al. 2014).

OMs can be applied to data collected before, during, and after operational programmes (MacKenzie & Bertoia 2024). This would require dynamic occupancy models, which allow occupancy to change between primary survey intervals by estimating colonisation and extinction probabilities (MacKenzie et al. 2002). Dynamic models have been applied to amphibians, carnivores, and small mammals to capture temporal variation in site use, offering more realistic inference in systems where occupancy is expected to change over time (MacKenzie et al. 2002; Miller et al. 2011; Sutherland et al. 2014). These models still rely on a closure assumption within each interval (i.e. site status does not change during repeated surveys within a season), but they can better accommodate temporal variation in site use across longer timescales, allowing for separate estimates of p for each stage of the eradication programme.

However, estimating p when the population density is low, and therefore the number of detections is small, can be very difficult, if at all possible. An alternative is to use independent information on detection probability from other sources at known low densities at a specific grid-cell size, in which case these values can be incorporated directly, and the model would then only be used to estimate the probability of occupancy. This flexibility can partially overcome issues of estimating parameters at inappropriate densities or data sparsity, but it shifts the burden of reliability onto the external estimates of p .

Accurate estimation of p is critical and often challenging because detection probabilities can vary substantially across habitats, detection devices, and seasons (Vattiato et al. 2023). This variation exposes important knowledge gaps, particularly for species and habitats where detection has been poorly quantified, limiting the reliability of occupancy models when used for proof of absence. It should be pointed out that these knowledge gaps in detection probability are not just common to occupancy models.

Occupancy modelling provides estimates of species presence at the grid-cell level, which may be too fine to reliably detect rare or transient individuals, especially in low-density populations. Although surveying many grid cells increases the likelihood of detecting such individuals somewhere across the landscape, the method may still fail to identify their presence at specific sites owing to their low numbers, temporary occupancy, or high mobility. As a result, occupancy estimates can underestimate true occupancy at fine spatial scales, limiting the ability to definitively confirm absence at individual sites.

A related issue with occupancy models is the selection of a grid-cell size, the choice of which is not always obvious in practice. Both ψ and p are dependent on, and will vary with, grid-cell size. The size is often chosen pragmatically to balance biological relevance with sampling feasibility; for example, aligning sites with average home range size, expected movement distances during the survey period, or the effective sampling area of detection devices (MacKenzie et al. 2006; Guillera et al. 2014). So, while individual home range is not an explicit parameter (as it is with the proof of absence model), the choice will reflect home range implicitly. Furthermore, selecting a size that is too large risks smoothing over fine-scale variation in species presence, while a small grid-cell size can lead to excessive zeros and unstable parameter estimates. It is important to note that grid-cell size must be defined once and must not change throughout the project.

Finally, field work to estimate the parameters for OM can be resource intensive. Reliable absence inference typically requires repeated surveys across many sites, which may not be feasible in remote or rugged terrain (Garrard 2008). The method is also sensitive to model misspecification, such as assuming constant detection when it varies with observer or environmental conditions, which can bias estimates of both ψ and p (Lahoz-Monfort 2014).

2.2 Proof of Absence model

The Proof of Absence (PoA) model is a framework that was developed specifically to quantify the probability that a species has been eradicated from a defined area given survey data (Anderson et al. 2013; Anderson et al. 2022a). Detection is typically defined as a continuous function of distance from a detection device or surveillance point using a g_0 - σ modelling approach (see below). It can also include grid-cell-level probabilities of detection, as with OM, where an animal is either detected or not within a cell during a survey period. The PoA model combines survey effort, detector layout, assumptions about detection probability, and habitat selection to estimate the probability that an individual in the eradication area would have been detected if present. This

information is then combined with a prior probability of species absence using Bayesian updating to estimate a probability of eradication.

2.2.1 g_0 - σ based method

The g_0 - σ framework is a statistical modelling approach that explicitly models detection as a declining function of distance from a detection device or surveillance point. Inference on the probability of eradication comes from combining knowledge of animal movement scale (σ) and baseline detectability (g_0) to model the probability of missing individuals given survey layout and effort.

These methods were originally developed from spatially-explicit-capture-recapture (SECR) frameworks (Efford & Fewster 2013) and are based on individual movement and distance-based detection processes. This approach differs fundamentally from OM in some of its assumptions and outputs. OM does not incorporate known information about spatial patterns in animal movement behaviour. In contrast, g_0 - σ methods allow inference over space by explicitly modelling how detection probability declines with distance from a detection point (Efford & Fewster 2013). This spatial foundation makes g_0 - σ models scale independent and robust to detector placement.

The models are built around two key parameters:

- g_0 : the baseline detection probability (i.e. nightly) of a device placed at the centre of an animal's home range.
- σ : a spatial scale parameter that describes the decrease in the probability of detection with increasing distance from the detection device, which is related to the home-range size of the species.

Together, these parameters define a spatial detection function. Armed with estimates of these parameters, it becomes possible to estimate the probability of detecting an animal anywhere in a defined area, given a known detector layout and survey effort (e.g. number of devices and length of deployment). This is done by aggregating the detection functions from multiple devices to construct a spatially explicit surface of surveillance sensitivity. This surface can be further summarised to produce the system-level sensitivity (SSe), which is the probability of detecting an animal in the study area. The method is flexible and enables detection functions from different types of surveillance devices and methods to be combined in a consistent manner.

In New Zealand, g_0 - σ methods have become increasingly important in predator control and eradication planning, especially for species such as mustelids, rodents, and possums. For example, Ramsey et al. (2011) used spatial detection models to evaluate the likelihood of possum absence on offshore islands after eradication efforts. Clayton et al. (2011) applied similar models to estimate the probability of detecting stoats post-eradication on Resolution Island. These examples show how g_0 - σ frameworks can inform strategic decisions about declaring eradication success or allocating further surveillance effort.

A strength of g_0 - σ methods is their robustness to deviations from idealised assumptions. While early models assumed circular, isotropic home ranges, Efford (2019) demonstrated that SECR-based models are resilient even when animals exhibit irregular movement patterns shaped by terrain, habitat, or other landscape features. This makes g_0 - σ based inference viable in real-world environments, where movement is rarely uniform or symmetrical.

Similarly, PoA frameworks can incorporate habitat-based risk models by adjusting the spatial detection surface in relation to habitat features, past detections, or resource distribution. For

example, higher detection probabilities may be assigned to habitat types or areas where animals are more likely to occur based on prior studies or habitat selection models. This integration creates a spatially irregular detection surface that improves the efficiency of surveillance by prioritising high-risk zones, complementing the spatially explicit detection framework inherent in g_0 - σ models (Ramsey & Efford 2010).

Estimates of g_0 and σ can be obtained from SECR analyses of telemetry or capture–recapture data (Vattiato et al. 2023), but other approaches are possible. For example, detection kernels can be approximated from empirical studies of movement and detection in similar systems (Anderson et al. 2022b; Anderson et al. 2016). This flexibility allows PoA to be applied even when estimates from SECR data are not directly available, which requires the assumption of parameter generality across systems.

2.2.2 Grid-cell methods

The PoA model can also include data from a grid-cell framework. An example application is the potential passive surveillance from the public (Anderson et al. 2022a). In this case, detection is defined at the level of a grid cell: an animal is either detected or not within that cell during a survey period. The PoA approach then combines detection probabilities across devices, cells, and survey occasions to estimate the probability that at least one individual would have been detected had it been present in the area.

The key inputs are the assumed grid-cell level detection probability ($p_{\text{detection}}$) which is based on number of devices and spatial coverage within a grid-cell. By combining these inputs, PoA provides managers with an interpretable metric of confidence that eradication has been achieved, or that the area is free of the species of concern.

The main limitation of grid-cell PoA methods is that they treat detection at the cell level as binary, abstracting away underlying processes such as movement or ranging behaviour. As such, grid-cell methods are highly dependent on the assumed value of $p_{\text{detection}}$ and on how representative that value is for the local context. Nevertheless, the framework is simple, transparent, and widely used in eradication programmes because it links directly to management decision making. They are typically used alongside g_0 - σ methods to allow for the inclusion of surveillance methods that are not point-based locations (e.g. public reports and mobile surveillance).

2.2.3 Rapid Eradication Assessment

Rapid Eradication Assessment (REA; Samaniego et al. 2013; Russell et al. 2017) is a streamlined g_0 - σ approach that uses g_0 and σ to provide rapid, operationally relevant assessments of eradication confidence. It is conceptually similar to the PoA model, but lacks the flexibility to incorporate any kind of surveillance data and is not computationally optimised to analyse large spatial data sets. Its appeal is that it can be applied rapidly to guide operational decisions and reporting. Similar to the PoA, REA can leverage habitat-based information by using prior knowledge of areas with high occupancy probability to guide rapid deployment of detectors. Incorporating habitat covariates can help ensure surveillance targets zones with the highest likelihood of residual individuals.

2.2.4 When to use g_0 - σ methods

Frameworks based on g_0 - σ , such as the PoA model, are particularly appropriate when the management objective is to make spatially explicit, probabilistic statements about absence, especially over large, continuous areas with heterogeneous terrain or incomplete detector coverage. Unlike occupancy models, which treat sites as discrete and implicitly assume uniform detection within a grid cell, g_0 - σ approaches model detection as a continuous function of distance from an individual's (latent) activity centre. This spatial explicitness is critical in eradication or containment efforts, where declaring success based on non-detection requires quantifying how likely it is that an animal, if present, would have been detected given the survey effort.

For example, consider an eradication programme targeting stoats on a rugged offshore island in New Zealand. Suppose trail camera traps are placed irregularly due to access limitations – denser along coastal tracks but sparse in steep interior forest. Occupancy models would struggle here: they assume discrete grid-cell boundaries and usually require repeated visits to estimate detection probability. Also, they cannot easily account for the variable distances over which an animal might encounter detectors or the spatial heterogeneity in movement paths.

In contrast, g_0 - σ methods allow surveyors to incorporate knowledge of stoat movement behaviour (e.g. from telemetry or previous SECR studies) to estimate how far individuals range and how likely they are to trigger a trap at various distances. With these parameters, managers can quantify expected detection probabilities for different locations and assess whether the absence of detections across the entire island – despite uneven trap spacing – still provides sufficient evidence to declare the population absent. This capability makes g_0 - σ modelling a better fit for landscapes and objectives where fine-scale spatial variation and realistic animal movement are central to making reliable inferences from non-detection data.

2.2.5 Limitations of g_0 - σ methods for probability of species eradication

Although g_0 - σ methods are well suited for inferring absence, they have important limitations. A primary challenge is the availability of robust, habitat-specific estimates for both g_0 and σ , particularly for lesser-studied predators or remote environments. As mentioned earlier, estimates can be obtained from SECR studies and other specific telemetry studies. Vattiato et al. (2023) provides a summary of various parameter values from a wide range of species and habitats. However, because estimates of detectability (as parameterised by g_0 and σ) are generally 'plugged-in' from other studies (rather than estimated as part of the monitoring, as is the case for occupancy models), parameter values may not be appropriate for the study area. Many species–habitat combinations still lack empirical estimates, forcing managers to rely on values from similar systems or to use conservative assumptions. Even when these parameters are derived from field studies in the same habitat type, managers must still be sure the estimates are generalisable to their own situation.

Another issue arises at very low densities: while the inverse relationship between density and home-range size is well described (Efford et al. 2016; Vattiato et al. 2023), individuals may not maintain stable home ranges when conspecifics are scarce, and may instead adopt migratory or transient movement in search of mates or resources. In such cases, the assumption of a fixed activity centre may become biologically unrealistic. Nevertheless, when σ is large relative to the detector layout, the model effectively assumes uniform space use, meaning the animal is equally likely to be detected anywhere in the array. As with all models that quantify the probability of eradication, assumptions must be made about the behaviour of the last few survivors. If we assume they are wide ranging, detection will be easier (large σ), whereas if we assume a single pregnant female or a mother with dependent offspring confined to a small home range, detection

will be harder (small σ). The flexibility of the framework allows these contrasting scenarios to be represented, and their consequences for eradication confidence to be explored explicitly.

One way to address these challenges is through site-specific calibration of detection parameters, or by using sensitivity analyses to evaluate how absence inferences change across a range of plausible g_0 and σ values. In contexts where movement may be more complex (e.g. animals switching between resident and exploratory states), multi-state models can represent such dynamics explicitly (Ergon & Gardner 2014; Kendall et al. 1997). These approaches do not remove the need for assumptions, but they provide a structured way to explore their consequences and improve the biological realism of eradication models, especially when dealing with survivors of control operations or re-invading individuals.

2.3 Random walk model

A Random Walk model is an individual-based model that is used to simulate the paths of individual animals across space and time. Typically, one or more simulated individuals are ‘released’ into a virtual landscape with simulated detection devices. Their direction and travel distance at each time-step are simulated to reflect actual animal movements in order to construct movement paths for each individual. Detection occurs when a simulated trajectory intersects with a detector’s effective range, typically formalised as a two-step process: an encounter probability (p_{enc}) that an animal comes within range of a detector, and an interaction probability (p_{int}) conditional on encounter that the animal is actually detected or triggers the device. Absence inference arises by modelling detection as an emergent property of simulated behaviour rather than a fixed probability tied to sites or distances.

These simulations can incorporate habitat-based risk layers or resource distributions to represent movement more realistically. For example, the Spatial Possum Model (Ramsey & Efford 2010) simulates individual possum trajectories while accounting for habitat features and areas of elevated disease transmission risk. This allows managers to identify locations where detection or control is most likely to be successful, enhancing absence inference in heterogeneous landscapes where animal movement and detectability are non-uniform.

Random walk approaches have been applied in contexts where fine-scale movement behaviour strongly influences the likelihood of detection. They can help assess the probability of detecting remnant populations, guide the placement of traps or camera arrays, and explore how landscape features or habitat modifications affect both movement and detectability. A random walk model for possums has been developed for Predator Free Dunedin to help guide trap and device layouts.¹

Despite their flexibility and realism, random walk methods have important limitations. They are computationally intensive, especially for large landscapes or many individuals. Their main limitation in this context is that their accuracy depends on detailed information about movement behaviour, habitat selection, and encounter and interaction probabilities. Outputs can be very sensitive to assumptions about home-range fidelity and behavioural responses to risk or habitat, and stochasticity in simulated paths often requires multiple runs to obtain stable estimates of detection probability and absence confidence. The movement data required to parameterise models of animal movements are very limited, and are often derived from only a small number of GPS-tracked animals, and only for a limited number of species, habitats, and population densities.

¹ <https://www.predatorfreedunedin.org/research/new-monitoring-research-will-move-us-closer-to-possum-eradication>

Despite the appearance of more accurate modelling of movements, they share the same limitation as the g_0 - σ approach in that there is very limited knowledge on how surviving individuals utilise their habitat.

3 General considerations

3.1 Bayesian extensions

Bayesian methods offer a flexible extension to traditional occupancy models and spatial detection frameworks such as g_0 - σ by explicitly incorporating uncertainty and prior knowledge into inference. Bayesian approaches provide a probabilistic framework that enhances existing models, particularly in contexts where data are sparse, detection is imperfect, and decisions must be made with incomplete information.

In a Bayesian OM framework, prior distributions are specified for parameters such as detection probability (p), occupancy probability (ψ), or covariates influencing presence and/or detection. As surveillance data accumulate – either spatially (across sites) or temporally (over repeated visits) – Bayesian updating refines these priors into posterior distributions, which form the basis for inference and decision making. This approach is especially useful for adaptive management, where monitoring is ongoing and decisions (e.g. whether to intensify surveillance or declare eradication success) must be made dynamically.

Bayesian frameworks have become central to quantifying confidence in eradication success, especially when relying on zero-detection data. The g_0 - σ approach uses Bayesian updating to combine prior information on species eradication with the SSe to derive the posterior probability of eradication. These methods typically combine prior information (e.g. on control efficacy), population dynamics (e.g. growth or reinvasion risk), and the performance of the surveillance network to estimate the probability of population absence (Gormley et al. 2021; Barnes et al. 2021; Barnes et al. 2022). Bayesian stochastic models have been applied to diverse systems to evaluate eradication outcomes and optimise monitoring: bovine TB in New Zealand possums (Anderson et al. 2013), stoat control on Resolution Island (Anderson et al. 2016), and nutria eradication in the USA (Anderson 2022a).

While simulation-based approaches allow flexibility in modelling detection processes under uncertainty, recent work has developed analytical solutions that enhance transparency, computational speed, and interpretability. For example, Barnes et al. (2021) and Barnes et al. (2022) derived closed-form equations to estimate the probability of eradication success based on cumulative surveillance effort, species-specific detection parameters (e.g. g_0 and σ), and assumptions about population growth or reinvasion. These models enable users to explore how the interplay between detection probability, effort, and population dynamics affects confidence in absence. Also, Gormley et al. (2021) and Anderson et al. (2022a) present practical tools that managers can use to calculate required effort thresholds for declaring eradication or to assess the performance of their surveillance systems under different scenarios.

3.2 Estimates of detection

In many ecological systems, assumptions underlying standard occupancy models or g_0 - σ spatial methods may not hold. Detection probability may vary with distance, observer, terrain, or individual behaviour – factors particularly relevant in New Zealand's rugged landscapes and highly variable ecosystems. Hybrid methods that combine elements of multiple frameworks have emerged to improve inference in these contexts.

3.2.1 Occupancy modelling and distance sampling

Distance sampling explicitly models the decline in detection probability with distance from the observer (Buckland 2015; Farr 2021). When integrated with OM, it allows for more accurate estimates of occupancy by accounting for spatial variation in detectability.

Point-count surveys of native birds such as kākā, kākāriki, and tūī in Pureora Forest and the Kaweka Range have used hybrid occupancy-distance models (Greene & Efford 2012). These combine traditional OM with detection functions based on distance sampling. In dense forest habitats, where detection varies greatly with vegetation and topography, such models outperform basic OM by accounting for missed detections further from the observer.

In Arctic ecosystems, Pedersen et al. (2012) applied a dual approach to monitor Svalbard rock ptarmigan by combining distance sampling to estimate density and OM to assess habitat use. Their analysis demonstrated that occupancy estimates were sensitive to habitat quality and year-specific detection probabilities, highlighting the importance of accounting for spatial and temporal variation in detectability. The study recommended integrating the two methods for more robust monitoring outcomes.

OM combined with distance sampling can be the most appropriate OM-based approach for modelling proof of absence in scenarios where detection probability varies significantly with distance from the observer, which is common in visually or acoustically based surveys. Standard OM assumes constant detectability or uses covariates to adjust for it, but this can result in biased absence inference when individuals are missed due to spatial variation in detection (MacKenzie 2002; MacKenzie 2006). Distance sampling explicitly models this decline using detection functions, improving the reliability of occupancy estimates by correcting for under detection at greater distances (Buckland et al. 2015). This approach is especially valuable when individual identification is not feasible, making it preferable over SECR methods for unmarked species such as vocal birds or cryptic mammals. When survey protocols collect detection distance information – such as point-counts or line transects – integrating distance sampling into OM provides a natural extension that increases precision (Pedersen et al. 2012). Also, in low-density populations or at the edge of a species' range, this method reduces the risk of incorrectly inferring absence due to low encounter rates (Guillera-Aroita 2017).

However, this hybrid method has its limitations. Species that alter their behaviour in the presence of observers – such as birds that flush early or remain silent – can violate the assumptions of both OM and distance sampling, leading to biased estimates of detection. Accurate distance estimation is essential, and measurement errors can further bias detection functions (Buckland et al. 2015). Moreover, distance sampling assumes that all individuals at distance zero are detected with certainty, which may not hold in dense habitats or when species are highly cryptic (Efford 2004). Thus, OM with distance sampling is best suited to studies where spatial variation in detectability must be addressed, spatially explicit methods are impractical, and assumptions about observer effects and detection distance can reasonably be met.

3.2.2 Occupancy modelling and capture–recapture

When individual identification is possible, capture–recapture models can be integrated with occupancy frameworks to estimate detection heterogeneity across sites and individuals. While more data intensive than traditional occupancy models, SECR avoids many of the biases associated with treating occupancy as a surrogate for density – biases that stem from unmeasured variation in detection probability, home-range size, and animal movements across plot boundaries (Efford & Dawson 2012).

Efford and Dawson (2012) caution that non-spatial occupancy models often confound detection probability with plot size and movement behaviour, making them unreliable proxies for density, particularly when animals are lured or attracted to traps or cameras, as is common in New Zealand predator control. Hybrid approaches combining widespread, low-cost detection sampling with more intensive local estimates of abundance, as proposed by Conroy et al. (2008), offer a possible alternative. Their two-phase sampling design uses occupancy detection data across many sites to identify where intensive capture–mark–recapture (CMR) should be conducted. A joint model then relates abundance at intensively sampled sites to detection at all sites, allowing estimation of abundance – including at sites without CMR data – through an abundance–detection relationship.

This approach is particularly well suited to rare or patchily distributed species, where sampling in all patches is impractical, but a robust, landscape-scale estimate of abundance, and therefore stronger inference about true absence, is still required. The Bayesian framework used by Conroy et al. (2008) supports posterior inference for detection, capture probability, and abundance while accounting for individual and spatial heterogeneity. This makes such hybrid models especially valuable for proof-of-absence contexts, where conventional occupancy methods alone may lack sufficient power or reliability.

3.3 Emerging detection methods: eDNA and acoustic detection

While traditional OMs and g_0 - σ frameworks have formed the backbone of species surveillance in New Zealand, new technologies are increasingly being used to complement and extend these approaches, particularly for cryptic, low-density or elusive species. Two of the most promising are environmental DNA (eDNA) sampling and passive acoustic monitoring, both of which allow detection without requiring direct observation or capture. These tools are particularly useful in habitats or taxa where visual or trapping methods are logistically challenging or ineffective.

eDNA sampling, which involves detecting trace DNA left by organisms in water, soil, or air, has been used to detect aquatic and semi-aquatic species such as invasive fish, frogs, or invertebrates. Its uptake in conservation has been rapid (Moss et al. 2022; Beng & Corlett 2020), including in New Zealand (Bird et al. 2024). eDNA can be extremely sensitive, capable of detecting organisms at very low densities and even when individuals are no longer present. However, its reliability for proof of absence depends on careful control of sampling and processing error, and it is inherently limited by DNA transport, degradation, and site-specific shedding rates. For this reason, modelling approaches often include covariates for environmental conditions, transport processes, and lab-based detection limits. Bayesian occupancy models with detection error structures, or hierarchical models that separate site-level presence from sample-level detection, are increasingly being used for eDNA data (Diana et al. 2021; Allen 2021; Stratton et al. 2020; Schmidt et al. 2013). These approaches treat observations as arising from a nested process: whether the species is present at the site, whether its DNA is present in the sample, and whether that DNA is detected. False-positives from eDNA are another factor that needs to be accounted for.

Similarly, acoustic methods have been widely adopted in New Zealand for monitoring bats, frogs, birds, and even some invasive species. Long-tailed bats (*Chalinolobus tuberculatus*) in the South Island are commonly surveyed using passive acoustic recorders that detect echolocation calls (Borkin et al. 2023). Traditional occupancy models have been applied to estimate presence across forest fragments, but detection probability varies substantially with time of night, weather conditions, ambient noise, and device type or placement (Mac Aodha et al. 2018). To address these issues, recent studies have incorporated detection covariates into occupancy frameworks (Petersma et al. 2024; Lucas et al. 2015), or used repeated measures to estimate detection probability more robustly (Clement et al. 2014).

Spatially explicit g_0 - σ methods have been successfully adapted for acoustic data using microphone arrays, a class of models known as acoustic spatial capture–recapture (ASCR) (van Dam-Bates et al. 2024; Wang et al. 2024; Stevenson et al. 2015; Efford et al. 2009). These methods allow density estimation from spatially structured detections, even without individual identification, by treating vocalisations as marked Poisson processes. However, in many systems – including bat monitoring – linking detections to individuals via echolocation remains challenging, limiting the application of ASCR to species or contexts where vocal individuality or array resolution is sufficient (Petersma et al. 2024).

In summary, emerging methods such as eDNA and acoustic detection provide valuable alternatives or complements to traditional surveillance tools. When thoughtfully integrated with occupancy or spatial models, they offer scalable and sensitive approaches for monitoring elusive species, especially in rugged or remote regions where New Zealand’s biodiversity is often concentrated. However, in order to make an assessment about the probability of species eradication, robust estimates of the various detection probabilities are required, as is, more specifically, the probability of detecting a species when it only remains at very low numbers.

4 Integrating different detection probabilities across frameworks

4.1 Why integration is needed

In the monitoring of eradication programmes species may not be truly absent, but we lack sufficient power to detect them. This difficulty is compounded by the fact that different survey tools yield different probabilities of detection, which can also differ depending on the ecology of the target species and the characteristics of the habitat. Thus, integrating multiple detection methods is often necessary.

Consider a forested reserve where conservationists are trying to determine whether an invasive rodent species has been eradicated. A camera trap might readily detect nocturnal foraging behaviour but fail if the animals are wary of infrared flashes. Acoustic detectors may help if the rodents emit vocalisations, but only if those vocalisations are frequent, loud, and distinct from background noise. Meanwhile, detection dogs might find scent trails even in low-density populations, especially in rugged or cluttered terrain where human observers or equipment struggle. Each of these methods produces a different detection probability, yet none alone may be high enough to confidently infer absence, or might be too expensive to use for large-scale surveillance.

But together, their strengths become complementary. Even if each device has a relatively low probability of detection, combining their outputs in a unified framework can dramatically improve the probability of detecting the species if it is present. This integration is especially valuable in

cases where failure to detect could lead to inappropriate management decisions, such as prematurely declaring success in an eradication programme or failing to trigger protective measures for a cryptic endangered species.

Moreover, environmental conditions can influence detection differently across methods. For example, acoustic detection might be compromised in windy conditions, while dog searches could remain effective. Conversely, visual surveys might be difficult in dense understorey, while automated sensors continue operating. All three general approaches covered in section 2 can combine detection probabilities from multiple methods in a consistent manner.

Gormley et al. (2011) used a combination of pellet transects, camera traps, and opportunistic sightings to search for sambar deer in Victoria, Australia, then applied OMs to estimate occupancy and detection probabilities, and used this information to estimate current and potential distribution. Other OM studies have combined acoustic and visual recording devices for frog monitoring (Rich et al. 2019), track plates and cameras for carnivores (Nichols et al. 2008), and camera traps with detection dogs (Glen et al. 2024).

Detection data from multiple tools can then be integrated in different ways to estimate the probability of eradication. For example, Kéry and Schaub (2011) provided a general Bayesian hierarchical framework for incorporating various observation processes – such as visual sightings, scat surveys, and sensor detections – into a unified model that accounts for method-specific detection probabilities and hierarchical structure in the data (e.g. spatial or temporal nesting).

The proof of absence model has been applied in a number of cases where a range of detection methods were used, including fixed devices such as trail cameras, as well as mobile search methods (Anderson et al. 2022a, Ramsey et al. 2023).

5 Model performance at very low population densities

5.1 Theoretical challenges

When populations decline to very low densities it becomes difficult to estimate parameters associated with detection probabilities. The fundamental problem is that number of detections become so low that even repeated, well-planned surveys can easily miss the species entirely, despite its continued presence in the area. Under these conditions the encounter process that underlies all detection models becomes rare. The mechanisms of encounter – be they camera triggers, trap captures, visual sightings, or audio detections – are probabilistic events. When individuals are sparse on the landscape, their movements may simply never intersect with the detection field, particularly if the duration or spatial extent of sampling is limited.

Models that assume a uniform baseline detection probability given presence become unreliable, because the assumption itself fails. At extremely low densities, even large increases in survey effort often produce diminishing returns. For example, doubling the number of camera traps or trap nights might only marginally increase the cumulative probability of detection when individuals rarely enter the effective detection area. This non-linearity means that unless additional information is brought in – such as strong prior beliefs, auxiliary telemetry data, or habitat-based risk predictions – the model's output tends to remain indecisive or misleadingly confident in absence (MacKenzie et al. 2002; Tyre et al. 2003).

Given that it is difficult to estimate parameters at low density, assumptions must be made about how to make inferences when no detections are found. There is evidence for animals increasing home ranges at low density and covering large areas (Vattiato et al. 2023), but there is also anecdotal evidence for small home ranges, especially peri-natal females, who are the main concern.

The appendix provides a design framework for estimating detection probabilities for species at low levels that will be applicable for a probability of eradication setting.

Models estimating the probability of eradication aim to give us a level of confidence to declare success and reallocate resources to other management issues. These models will never tell us with certainty that eradication has been achieved. All models in science make assumptions, and the interpretation of model predictions must be conditioned on the assumptions that were made. For example, in assuming wide-ranging individuals, the resulting probabilities of eradication must be interpreted accordingly.

5.2 Impact on different models

5.2.1 Occupancy models

Occupancy models were designed to account for imperfect detection by estimating both the probability of occupancy (ψ) and the conditional probability of detection (p). A strength of OMs is that detection probability is estimated explicitly from surveillance data; however, some level of detections and repeat detections are required. In theory, the framework can handle sparse detections, but in practice very low-density scenarios push the model to its limits. Consider a sole-surviving pregnant female that ranges over a much larger area than animals that were detected in the OM parameterisation phase. The probability of detecting this animal in any given grid cell will be lower than the estimated p , but the animal will pass through many more grid cells and potentially have a greater chance of being detected over a wider spatial range. The sensitivity of the resulting probability of eradication to this change in behaviour has not been tested.

When species are at very low density there may be zero detections, which can make estimation of ψ and p very difficult: without 'detections' these data could arise due to the species being absent, or the species being present but undetectable. Auxiliary data, including prior information on detection probabilities, would be needed.

5.2.2 g_0 - σ models

Spatially explicit models such as those using the g_0 - σ formulation are similarly vulnerable under low-density conditions. These models assume that detection probability declines with distance from an individual's activity centre, and that animal movements are captured by the parameter σ , which represents the spatial scale of movement. However, these assumptions may not hold, especially if individuals respond behaviourally to low conspecific density.

At low density animals often increase their home range size in search of resources or mates. This behavioural shift effectively increases σ and will reduce the probability of encountering a given detector, but will increase the probability of encountering one or more of the array of detectors. The result is an overall increase in the probability of detecting the individual (Anderson et al. 2022b) somewhere in its range. Consequently, when the user of the PoA model assumes a wide-ranging survivor that the surveillance system is trying to detect, the resulting probabilities of detection and therefore eradication will tend to be higher than when it is assumed that the survivor is moving in a

small home range. This can be countered by decreasing g_0 , but it can be unclear what level is required.

5.2.3 Empirical findings

Field studies and simulation exercises alike confirm these challenges. Several studies have shown that at low densities, survey effort needs to be exceptionally high or models need to be fortified with external data sources to confidently declare absence (Owens et al. 2024; Nathan et al. 2013).

Field studies have confirmed the difficulty of detecting low-density carnivores using standard survey durations. In alpine stoat surveys, for instance, Smith and Weston (2017) found that multiple night camera deployments often failed to record detections, even in areas where stoats were later confirmed to be present. Extending deployments improved detection, but gains were often modest, suggesting that simple increases in survey duration may not be sufficient when g_0 is very low. In contrast, more targeted strategies can produce greater improvements. Bled et al. (2013) demonstrated that incorporating prior information – such as telemetry-informed estimates of σ or habitat suitability layers – into dynamic occupancy models improved detection probability and inference efficiency, even with limited survey effort.

In short, while models are mathematically capable of accounting for imperfect detection, their performance in low-density scenarios is ultimately limited by the quality and quantity of data, and/or available estimates of detection probability. When the detection process itself becomes rare, more nuanced and information-rich designs – not just more sampling – are needed to draw meaningful conclusions about absence.

6 Conclusions

The ability to confidently declare a species absent following local eradication efforts is a cornerstone of effective invasive species management. As this review has shown, achieving such confidence is fundamentally constrained by imperfect detection, especially as population densities approach or are at zero. While surveillance models such as occupancy frameworks and PoA methods have made major contributions to post-eradication inference, each is vulnerable to parameter uncertainty and requires clearly stated assumptions.

One consistent theme emerging from the literature is the importance of explicitly accounting for detection uncertainty. Early models that assumed fixed and known detection probabilities are now broadly seen as inadequate for informing management decisions in challenging, real-world contexts. Bayesian and hierarchical extensions provide a more flexible foundation, allowing analysts to incorporate prior knowledge, model heterogeneity, and simulate uncertainty. Nevertheless, even these advanced approaches can fail to provide clear guidance when the data are sparse or the ecological system is highly variable, both of which are common in eradication scenarios.

The integration of multiple detection methods emerges as a clear and necessary evolution in surveillance design. No single tool – whether camera traps, acoustic sensors, detection dogs, or eDNA – is likely to be sufficient across all habitats, seasons, and behavioural states. Instead, multi-method frameworks offer a pragmatic way to leverage the complementary strengths of different tools. These approaches not only improve detection power but also help mitigate the risk of false absences that could otherwise derail eradication programmes.

Yet integration alone is not a panacea. The statistical frameworks used to combine data streams must be carefully chosen and adequately parameterised. Method-specific differences in detection probabilities, spatial coverage, temporal resolution, and cost all influence the overall surveillance outcome. Importantly, model performance at low densities depends not only on the tools used, but also on how well models capture ecological and behavioural changes that influence detectability. For example, as home ranges expand or movement patterns shift at low density, the assumptions made about animal movement behaviour will have an impact on the selection of g_0 and σ , and on the resulting probability of eradication. The uncertainty about animal behaviour and space use at very low densities will affect the reliability of all the modelling approaches discussed.

Several key gaps remain. There is a shortage of formal sensitivity analyses exploring model performance at very low densities under different surveillance designs, detection regimes, and risk tolerances. The empirical basis for many model parameters is limited, particularly in rugged, remote or understudied habitats. Greater effort is needed to generate and share empirical estimates of detection probability across contexts, and to systematically test how integrated models perform under realistic constraints. Simulation-based approaches, including decision-theoretic frameworks, provide a promising path forward for optimising survey design and minimising decision risk.

As eradication programmes scale up in complexity and ambition, surveillance strategies must keep pace. A flexible, multi-method approach that explicitly models uncertainty, integrates diverse data sources, and adapts to ecological variability offers the most robust path forward. Future research should prioritise developing generalisable integration frameworks, conducting power analyses tailored to local contexts, and filling knowledge gaps in detection parameters in very low density populations (see Appendix). By doing so, we can improve our capacity to detect rare individuals, support defensible declarations of absence, and enhance the long-term success of invasive species eradication efforts.

7 References

- Allen MC 2021. Terrestrial eDNA survey outperforms conventional approach for detecting an invasive pest insect within an agricultural ecosystem. *Environmental DNA* 3(6): 1102–1112.
- Anderson DP, McMurtrie P, Edge KA, Baxter PW, Byrom AE 2016. Inferential and forward projection modeling to evaluate options for controlling invasive mammals on islands. *Ecological Applications* 26(8): 2546–2557. <https://doi.org/10.1002/eap.1415>
- Anderson DP, Pepper MA, Travers S, Michaels TA, Sullivan K, Ramsey DSL. 2022a. Confirming the broadscale eradication success of nutria (*Myocastor coypus*) from the Delmarva Peninsula, USA. *Biological Invasions* 24: 3509–3521. <https://doi.org/10.1007/s10530-022-02855-x>
- Anderson DP, Ramsey DS, Nugent G, Bosson M, Livingstone P, Martin PA, Sergeant E, Gormley AM, Warburton B 2013. A novel approach to assess the probability of disease eradication from a wild-animal reservoir host. *Epidemiology and Infection* 141(7): 1509–1521. <https://doi.org/10.1017/S095026881200310X>
- Anderson DP, Rouco C, Latham MC, Warburton B 2022b. Understanding spatially explicit capture–recapture parameters for informing invasive animal management. *Ecosphere* 13(11): e4269. doi.org/10.1002/ecs2.4269
- Barnes B, Giannini F, Parsa M, Ramsey D 2021. Inferring species absence from zero-sighting records using analytical Bayesian models with population growth. *Methods in Ecology and Evolution* 12(11): 2208–2220.
- Barnes B, Parsa M, Giannini F, Ramsey D 2022. Analytical Bayesian models to quantify pest eradication success or species absence using zero-sighting records. *Theoretical Population Biology* 144: 70–80.
- Beng KC, Corlett RT 2020. Applications of environmental DNA (eDNA) in ecology and conservation: opportunities, challenges and prospects. *Biodiversity and Conservation* 29(7): 2089–2121.
- Bird S, Wilkinson S, McGaughan A 2024. Wetland biodiversity in Aotearoa New Zealand: an eDNA perspective on exotic and non-exotic species. *New Zealand Journal of Zoology* 52(4): 410–427.
- Bled F, Nichols JD, Altwegg R 2013. Dynamic occupancy models for analyzing species' range dynamics across large geographic scales. *Ecology and Evolution* 3(15): 4896–4909.
- Bomford M, O'Brien P 1995. Eradication or control for vertebrate pests? *Wildlife Society Bulletin* 23: 249–255
- Borkin KM, Giejsztowt J, McQueen-Watton J, Smith DHV 2023. Influence of weather on long-tailed bat detection in a North Island exotic forest. *New Zealand Journal of Ecology* 47(1): 3546.
- Buckland ST, Rexstad EA, Marques TA, Oedekoven CS 2015. Distance sampling: Methods and applications. Vol. 431. Cham, Springer.
- Clayton RI, Byrom AE, Anderson DP, Edge KA, Gleeson D, McMurtrie P, Veale A 2011. Density estimates and detection models inform stoat (*Mustela erminea*) eradication on Resolution Island, New Zealand. In: Veitch CR, Clout MN, Towns DR eds. *Island invasives: Eradication and management*. Gland, Switzerland, IUCN. Pp. 413–417.
- Clement MJ, Rodhouse TJ, Ormsbee PC, Szewczak JM, Nichols JD 2014. Accounting for false-positive acoustic detections of bats using occupancy models. *Journal of Applied Ecology* 51(5): 1460–1467.

- Conroy MJ, Runge JP, Barker RJ, Schofield MR, Fonnesbeck CJ 2008. Efficient estimation of abundance for patchily distributed populations via two-phase, adaptive sampling. *Ecology* 89(12): 3362–3370.
- Diana A, Matechou E, Griffin JE, Buxton AS, Griffiths RA 2021. An RShiny app for modelling environmental DNA data: accounting for false positive and false negative observation error. *Ecography* 44(12): 1838–1844.
- Efford MG 2004. Density estimation in live-trapping studies. *Oikos* 106(3): 598–610.
- Efford MG 2019. Non-circular home ranges and the estimation of population density. *Ecology* 100(2): e02580.
- Efford MG, Dawson DK 2012. Occupancy in continuous habitat. *Ecosphere* 3(4): 1–15.
- Efford MG, Dawson DK, Borchers DL 2009. Population density estimated from locations of individuals on a passive detector array. *Ecology* 90(10): 2676–2682.
- Efford MG, Dawson DK, Jhala YV, Qureshi Q 2016. Density-dependent home-range size revealed by spatially explicit capture–recapture. *Ecography* 39(7): 676–688.
- Efford MG, Fewster RM 2013. Estimating population size by spatially explicit capture–recapture. *Oikos* 122(6): 918–928.
- Ergon T, Gardner B 2014. Separating mortality and emigration: modelling space use, dispersal and survival with robust-design spatial capture–recapture data. *Methods in Ecology and Evolution* 5(12): 1327–1336.
- Farr MT, Green DS, Holekamp KE, Zipkin EF 2021. Integrating distance sampling and presence-only data to estimate species abundance. *Ecology* 102(1): e03204.
- Garrard GE, Bekessy SA, McCarthy MA, Wintle BA 2008. When have we looked hard enough? A novel method for setting minimum survey effort protocols for flora surveys. *Austral Ecology* 33(8): 986–998.
- Glen AS, Garvey PM, Innes J, Buchanan F 2024. What can wildlife-detection dogs offer for managing small mammalian predators? *Wildlife Research* 51(1): WR23068.
- Gormley A, Anderson DP, Lustig A, Latham CM, Howard S, Scroggie M, Ramsey DSL 2021. Quantitative decision support for eradication: a primer. Tech. rep. Manaaki Whenua—Landcare Research and Arthur Rylah Environmental Research Institute, Centre for Invasive Species Solutions, Canberra, Australia.
- Gormley AM, Forsyth DM, Griffioen P, Lindeman M, Ramsey DSL, Scroggie MP, Woodford L 2011. Using presence-only and presence–absence data to estimate the current and potential distributions of established invasive species. *Journal of Applied Ecology* 48: 25–34.
- Greene T, Efford M 2012. Birds: estimates of absolute density and abundance–distance sampling. Tech. rep. New Zealand Department of Conservation. Inventory and monitoring toolbox: birds, DOC/DM-534993.
- Guillera-Arroita G 2014. A critical review of the performance of species distribution models. *Ecological Modelling* 272: 1–15.
- Guillera-Arroita G 2015. Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogeography* 24(3): 276–292.
- Guillera-Arroita G 2017. Modelling of species distributions, range dynamics and communities under imperfect detection: advances, challenges and opportunities. *Ecography* 40(2): 281–295.

- Johnstone KC, Garvey P, Hickling GJ 2024. Invasive mammal control selects for trap-recalcitrant behaviour and personality. *Biological Invasions* 26: 549–564. <https://doi.org/10.1007/s10530-023-03191-4>
- Johnstone KC, Price C, Garvey PM 2024. Personality, sex and capture biases: Challenges for predator monitoring and management. *Journal of Applied Ecology* 61: 2207–2218. <https://doi.org/10.1111/1365-2664.14724>
- Kendall WL, Nichols JD, Hines JE 1997. Estimating temporary emigration using capture–recapture data with Pollock’s robust design. *Ecology* 78(2): 563–578.
- Kéry M, Royle JA 2016. *Applied hierarchical modeling in ecology: Analysis of distribution, abundance and species richness in R and BUGS*. Academic Press.
- Kéry M, Schaub M 2011. *Bayesian population analysis using WinBUGS: a hierarchical perspective*. Academic Press.
- Lahoz-Monfort JJ, Guillera-Aroita G, Wintle BW 2014. Imperfect detection impacts the performance of species distribution models. *Global Ecology and Biogeography* 23(4): 504–515.
- Lucas TCD, Moorcroft EA, Freeman R, Rowcliffe JM, Jones KE 2015. A generalised random encounter model for estimating animal density with remote sensor data. *Methods in Ecology and Evolution* 6(5): 500–509.
- Mac Aodha O, Gibb R, Barlow KE, Browning E, Firman M, Freeman R, Harder B, Kinsey L, Mead GR, Newson SE, et al. 2018. Bat detective—Deep learning tools for bat acoustic signal detection. *PLoS Computational Biology* 14(3): e1005995.
- MacKenzie DI, Bertoia A 2024. A data requirement primer for proof of eradication predator free programmes. Report for Predator Free 2050 Ltd. Client Report 188.
- MacKenzie DI, Nichols JD, Lachman GB, Droege S, Royle JA, Langtimm CA 2002. Estimating site occupancy rates when detection probabilities are less than one. *Ecology* 83(8): 2248–2255.
- MacKenzie DI, Nichols JD, Royle JA, Pollock KH, Bailey LL, Hines JE 2006. *Occupancy estimation and modeling: Inferring patterns and dynamics of species occurrence*. Academic Press.
- Miller DA, Nichols JD, Mcclintock BT, Grant EH, Bailey LL, Weir LA 2011. Improving occupancy estimation when two types of observational error occur: Non-detection and species misidentification. *Ecology* 92(7): 1422–1428.
- Moss WE, Harper LR, Davis MA, Goldberg CS, Smith MM, Johnson PTJ 2022. Navigating the trade-offs between environmental DNA and conventional field surveys for improved amphibian monitoring. *Ecosphere* 13(2): e3941.
- Nathan HW, Clout MN, Murphy EC, MacKay JWB 2013 Strategies for detection of house mice on a recently invaded island. *New Zealand Journal of Ecology* 37: 26-32
- Nichols JD, Bailey LL, O’Connell Jr AF, Talancy NW, Campbell Grant EH, Gilbert AT, Annand EM, Husband TP, Hines JE 2008. Multi-scale occupancy estimation and modelling using multiple detection methods. *Journal of Applied Ecology* 45(5): 1321–1329.
- Owens G, Gracanin A, Potts J, Young CM, Heinsohn R, Gibbons P, et al. 2024. Detection and density estimation for a cryptic species. *Austral Ecology* 49(2): e13467.
- Pedersen ÅØ, Bårdsen B, Yoccoz NG, Lecomte N, Fuglei E 2012. Monitoring Svalbard rock ptarmigan: distance sampling and occupancy modeling. *The Journal of Wildlife Management* 76(2): 308–316.

- Petersma FT, Thomas L, Thode AM, Harris D, Marques TA, Cheoo GV, Kim KH 2024. Accommodating false positives within acoustic spatial capture–recapture, with variable source levels, noisy bearings and an inhomogeneous spatial density. *Journal of Agricultural, Biological and Environmental Statistics* 29(3): 471–490.
- Ramsey DSL, Anderson DP, Gormley AM 2023. Invasive species eradication: How do we declare success? *Cambridge Prisms: Extinction* 1: e4. <https://doi.org/10.1017/ext.2023.1>.
- Ramsey DSL, Efford M, Ball S 2005. The evaluation of indices of animal abundance using spatial simulation of animal trapping. *Wildlife Research* 32(3): 229–237.
- Ramsey DSL, Efford MG 2010. Management of bovine tuberculosis in brushtail possums in New Zealand: predictions from a spatially explicit, individual based model. *Journal of Applied Ecology* 47(4): 911–919.
- Ramsey DSL, Parkes JP, Will D, Hanson CC, Campbell KJ 2011. Quantifying the success of feral cat eradication, San Nicolas Island, California. *New Zealand Journal of Ecology* 35(2): 163–173.
- Rich LN, Furnas BJ, Newton DS, Brashares JS 2019. Acoustic and camera surveys inform models of current and future vertebrate distributions in a changing desert ecosystem. *Diversity and Distributions* 25(9): 1441–1456.
- Rout TM 2009. Declaring eradication of invasive species: a review of methods for transparent decision-making. *Plant Protection Quarterly* 24(3): 92–94.
- Russell JC, Binnie HR, Oh J, Anderson DP, Samaniego-Herrera A 2017. Optimizing confirmation of invasive species eradication with rapid eradication assessment. *Journal of Applied Ecology* 54: 160–169. <https://doi.org/10.1111/1365-2664.12753>
- Samaniego-Herrera A, Anderson DP, Parkes JP, Aguirre-Muñoz A 2013. Rapid assessment of rat eradication after aerial baiting. *Journal of Applied Ecology* 50: 1415–1421. <https://doi.org/10.1111/1365-2664.12147>
- Schmidt BR, Kéry M, Ursenbacher S, Hyman OJ, Collins JP 2013. Site occupancy models in the analysis of environmental DNA presence/absence surveys: a case study of an emerging amphibian pathogen. *Methods in Ecology and Evolution* 4(7): 646–653.
- Smith DHV, Weston KA 2017. Capturing the cryptic: a comparison of detection methods for stoats (*Mustela erminea*) in alpine habitats. *Wildlife Research* 44(5): 418–426.
- Spiegel O, Leu ST, Bull CM, Sih A 2017. What's your move? Movement as a link between personality and spatial dynamics in animal populations. *Ecology Letters* 20(1): 3–18.
- Stevenson BC, Borchers DL, Altwegg R, Swift RJ, Gillespie DM, Measey GJ 2015. A general framework for animal density estimation from acoustic detections across a fixed microphone array. *Methods in Ecology and Evolution* 6(1): 38–48.
- Stratton C, Sepulveda AJ, Hoegh A 2020. msocc: Fit and analyse computationally efficient multi-scale occupancy models in R. *Methods in Ecology and Evolution* 11(9): 1113–1120.
- Sutherland, CS, Elston DA, Lambin X 2014. A demographic, spatially explicit patch occupancy model of metapopulation dynamics and persistence. *Ecology* 95(11): 3149–3160.
- Tyre AJ, Tenhumberg B, Field SA, Niejalke D, Parris K, Possingham HP 2003. Improving precision and reducing bias in biological surveys: estimating false-negative error rates. *Ecological Applications* 13(6): 1790–1801.

- van Dam-Bates P, Papathomas M, Stevenson BC, Fewster RM, Turek D, Stewart FEC, Borchers DL 2024. A flexible framework for spatial capture-recapture with unknown identities. *Biometrics* 80(1): ujad019.
- Vattiato G, Binny RN, Davidson SJ, Byrom AE, Anderson DP, Plank MJ, Carpenter JK, James A 2023. Detectability of ten invasive mammal pests in New Zealand: a synthesis of spatial detection parameters. *New Zealand Journal of Ecology* 47(1): 3552.
- Vattiato G, Garvey PM, Binny RN, Plank MJ, Gormley AM, Hickling GJ 2024. Optimising control device luring strategies for invasive predator control: A modelling approach. *Ecology and Evolution* 14(12): e70604.
- Vattiato G, Plank MJ, Binny RN 2021. Individual heterogeneity affects the outcome of small mammal pest eradication. *Theoretical Ecology* 14: 219–231.
- Wang Y, Ye J, Li X, Borchers DL 2024. Towards automated animal density estimation with acoustic spatial capture-recapture. *Biometrics* 80(3): ujae081.

Appendix 1 – Experimental design for estimate detection parameters

Background

The probability of ‘detecting our species of interest, in a defined area, within a specified time period, if it is present’, is defined as the system-level surveillance sensitivity (SSe). It is a measure of how good our surveillance system is, not an estimate of how likely it is that the species is present.² In the context of proving that an eradication attempt has been successful, we are asking if there were a single survivor (or perhaps two), what is the chance that we will detect it? If our surveillance is very poor (i.e. SSe is very low), then not finding a survivor does not really give us much extra confidence in eradication. In contrast, if our surveillance is intensive (i.e. SSe is very high), then not finding any survivors will greatly increase our confidence of eradication success.

SSe reflects the quality of the surveillance network. The value of SSe depends on a number of factors, including overall surveillance effort (e.g. number of devices, length of transect, and length of deployment, type of surveillance), as well as factors relating to the species itself (some species are more cryptic than others and harder to detect), population density (it is harder to detect the species when the density is very low), habitat type, and season.

There are some general relationships that hold. For example, SSe increases with both the length of the surveillance period and the number of devices; i.e. the longer and more intensive we look, the more likely we will detect any remaining individuals. Species with small home ranges typically need devices and/or surveillance transects spaced closer together than species with larger home ranges: few devices and large spaces between them and/or transects means an increased risk that surviving animals can exist undetected.

The overall SSe is calculated by aggregating up the detection probabilities of all the deployed individual devices, while accounting for the deployment length. We can also calculate the ‘system’ (i.e. number of devices and deployment length) required to achieve an SSe that will give enough confidence of absence if nothing is detected.

This requires estimates of the specific detection probabilities of each of the planned surveillance methods for the species of interest, and how they might differ across the habitats in the study area. These detection probabilities need to be estimated in the case of a single device detecting a single animal so that they can be aggregated and scaled in a consistent manner.

For the purposes of estimating probability of eradication, these detection probabilities should be estimated in situations where the species is at very low levels so that their behaviours reflect the intended use case.

² Note that in the proof of absence framework (section 2.2), SSe is combined with the prior estimate of the probability of species eradication using Bayes’ rule to calculate the posterior probability of a successful eradication.

Method

For devices in fixed locations, two events must occur to detect an individual animal: the individual must 'encounter' a detection device, and then 'interact' with it. Calculating the probability of individual detection requires estimates of both the encounter and interaction probabilities.

In the g_0 - σ approach, the probability of detection is a function of σ (related to an individual's home range size), and g_0 (the probability that a device placed at the home-range centre of an individual will detect it on a single night). This is given by:

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

where d is the distance from the home-range centre to the device. We can split g_0 into encounter (E_0) and interaction given an encounter (I_e):

$$g_0 = E_0 \times I_e$$

The probability that an individual encounters a single device depends fundamentally on how the individual moves in the landscape; i.e. the area it inhabits and the speed with which it moves across that 'home range'. If the movement rate is the same, individuals that inhabit large areas will have a lower chance of encountering a single device placed in its home range compared with an individual that inhabits a smaller area with a single device placed in its area. Encounter is therefore a combination of home-range and activity (i.e. for a given time period, the probability of the individual approaching within a specified distance of the device).

Given an encounter, the probability of interaction is defined as the probability of the individual interacting with the device in a way that results in a successful detection. The interaction may be passive, such as in the case of trail cameras (i.e. an individual just has to travel past the field of view in a manner that results in triggering the shutter and capturing the image of the animal), or active, as in the case of bite interference devices such as chew-cards (i.e. the individual must bite the card and leave an identifiable impression) or traps (i.e. the individual must trigger the trap in a manner that results in successful capture, or kill in the case of lethal traps).

So, although different devices will have different overall probabilities of detection, these differences are due mostly to the probability of interaction: factors such as habitat and season will influence movement and therefore the encounter probability, which will generally be independent of the device being deployed. Therefore, if we already know the encounter probability (E_0) of an individual for a given habitat and/or population density, then we only need to set up trials for measuring the various probabilities of interaction for new devices. However, encounter and home range are specific to density and habitat, and for populations at very low levels little is known about how they use the landscape. Therefore, estimating E_0 and habitat use for a species at very low levels across a range of habitats is important for parameterising the models.

Experimental trial design

Estimating encounter and habitat use

How individuals utilise and move across the landscape when at very low levels (e.g. one or two individuals) is largely unknown, and this will very much affect the probability of encounter. Therefore, estimating the nightly encounter probability (E_0) and the associated home range parameter (σ) of a species at very low densities requires measuring this at very low densities. A general approach is to fit individual animals with GPS collars combined with proximity sensors and monitor their movements in a landscape that contains proximity sensors deployed at known locations in order to detect when the individual has 'encountered' that fixed location.

There are two options to carry this out in practice. Option one is to release a small number of GPS/proximity-collared animals in an area previously free of the species. This could be a fenced area, ideally much larger than the natural range of an individual so as not to inhibit their natural movements, or an unfenced area free of the species. We note, however, that introducing the species into that previously free area would raise many other issues. A disadvantage of this general approach is that movements of the released individuals may not be an accurate reflection of the movements of an individual that survives intensive control.

A second option is to take an area of moderate density where intensive control is planned in the near future. Field technicians would capture as many individuals as possible and fit them with GPS/proximity collars, before releasing them back into the area. Lethal control would be carried out after all the releases in the hope that only a few survivors remain (to reflect a population at very low densities), all of which are collared individuals (so we can empirically measure their movements). The movements of these survivors would arguably be a closer reflection of reality than releasing an individual into a free area. There is, however, a risk that no collared animals survive the intensive lethal control, resulting in no data, or that substantial numbers of uncollared animals survive, meaning that the number of animals remaining is higher than the desired one or two 'survivors', and therefore their movements may not reflect the very low density situation.

GPS collars should be deployed for a significant length of time (e.g. at least 8 weeks) in order to obtain as much information on space use as possible. The time interval between fixes is a further consideration: short intervals (e.g. 5 minutes) would result in information on finer-scale movements that could also be useful for parameterising random walk models (section 2.3); however, this comes at the cost of a shorter battery life. Longer intervals (e.g. 6 hours) will provide more movement information, but this is likely to be too coarse, especially given aim of learning about space use of surviving individuals, which may be atypical of individuals with stable home ranges.

If successful, the data would be used to (i) obtain information on space use and movements at very low densities; (ii) provide information on whether the assumption of a stable home range holds, and if not, explore the effect of violation of this assumption in the modelling framework; and (iii) provide an empirical estimate of the encounter probability E_0 for the combination of species+habitat.

Estimating interaction

Calculating the interaction probability (I_e) for various devices is arguably more straightforward. Detection devices would be deployed in an area in conjunction with a trail camera set facing each one. This deployment set-up will allow for recording each entire 'encounter' event and thus determine whether an encounter results in an interaction; i.e. if an individual is within some specified distance of the device (10 m), does it then interact (e.g. bite a chew-card, or get caught in a leg-hold trap, or activate a camera being trialled)? Put simply, the proportion of encounters that result in an interaction during that day/evening is an empirical estimate of I_e for that specific device. There is a time component that must be considered given that g_0 is typically expressed as a nightly probability of detection: if an animal encounters the device but moves away without interacting, but returns later during the same evening and successfully interacts with it, then that is counted as a positive interaction for that initial encounter (not one interaction out of two encounters).

For both encounter and interaction, a decision needs to be made about what distance from the device is the start of the 'encounter'? For example, does a possum 'encounter' a leg-hold trap when it is within 10 m, or does it only recognise the object when within 1 m?

Combining estimates

As an illustrative example, imagine we were able to carry out trials to estimate encounter and home range of possums in three different habitat types: forest, shrubland, and grassland. Replicate trials were carried out in areas where only one or two possums remained. And suppose we obtain the estimates shown in the table below:

Table A1. Illustrative estimates of encounter E_0 and home-range scale parameter σ

Habitat	Encounter E_0	Home-range scale (σ)
Forest	0.4	120
Shrubland	0.2	200
Grassland	0.1	300

A set of separate trials was carried out to estimate the interaction probability of a range of devices, and the following results were obtained.

Table A2. Illustrative estimates of number of encounters, interactions, and interaction probability (I_E) for three detection methods

Device	Encounters	Interactions	I_E
Leghold-trap	60	12	0.2
Trail camera	80	32	0.4
Wax tag	40	10	0.25

We can then combine these to construct estimates of g_0 for the combination of habitat and device type.

Table A3. Illustrative estimates of encounter, interaction, and g_0 for combinations of habitat and device

Habitat	Device	E_0	I_E	g_0
Forest	Leghold-trap	0.4	0.2	0.08
Shrubland	Leghold-trap	0.2	0.2	0.04
Grassland	Leghold-trap	0.1	0.2	0.02
Forest	Trail cameras	0.4	0.4	0.16
Shrubland	Trail cameras	0.2	0.4	0.08
Grassland	Trail cameras	0.1	0.4	0.04
Forest	Wax tags	0.4	0.25	0.1
Shrubland	Wax tags	0.2	0.25	0.05
Grassland	Wax tags	0.1	0.25	0.025

When new devices are developed, subsequent trials would only need to focus on estimating the interaction probability.

How many trials would be required?

For estimating the encounter probability (E_0) and home-range scale parameter (σ) of a species at very low levels, separate trials would need to be carried out for each habitat where it is expected their movements might differ substantially, and potentially also by season. For each combination of these, it is recommended that at least 20 trials be carried out. The potential for individual variability means that the estimates for each animal may vary substantially, and it is therefore very important to determine that variability. Similarly, when estimating the interaction probability conditional on encounter, trials using at least 50 animals for each device type are recommended, but preferably more.