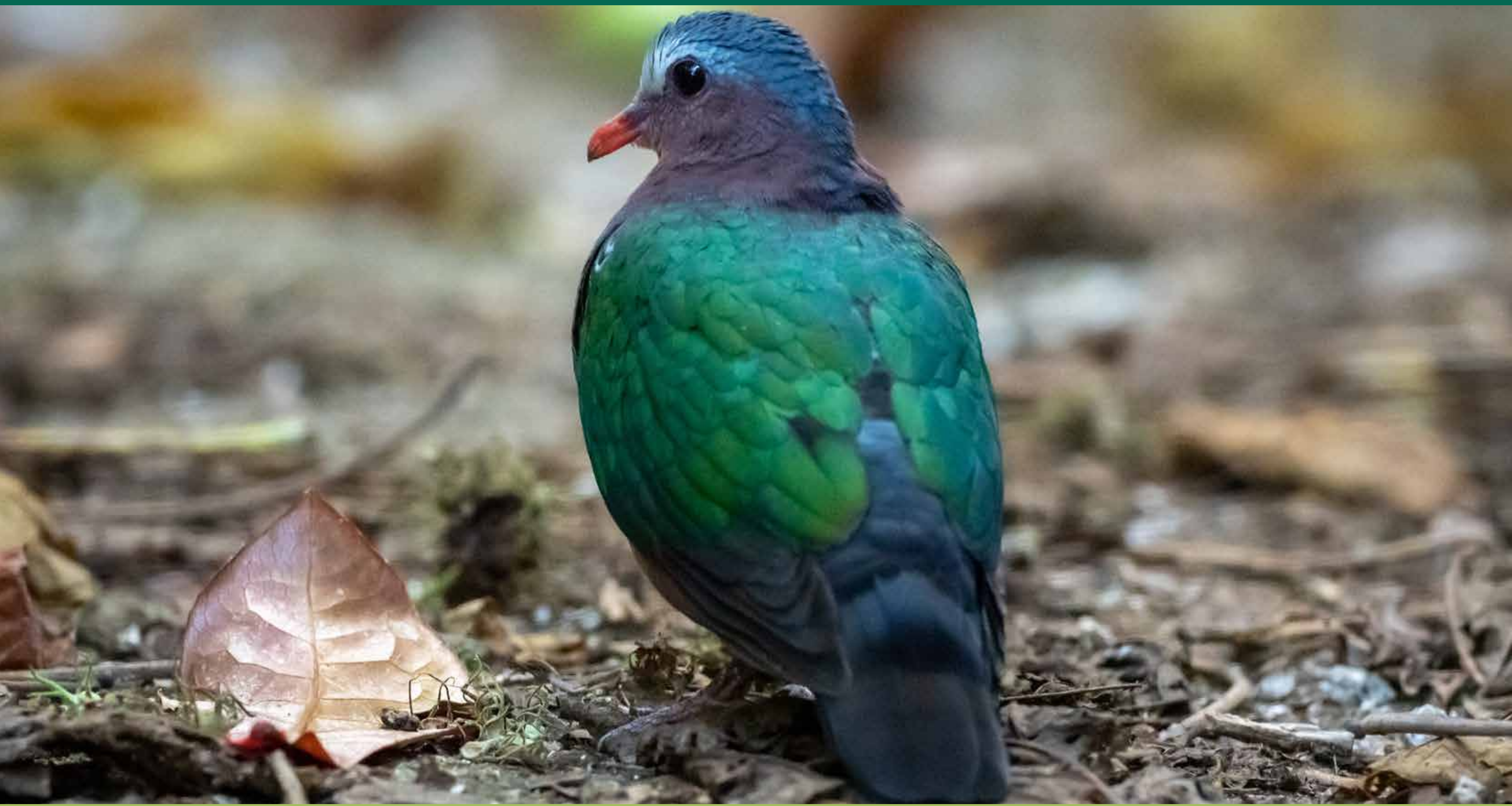
Threatened Species Recovery Hub

National Environmental Science Programme



Using power analysis and spatial prioritisation to optimise design of monitoring to detect population declines of forest birds on Christmas Island

Final Report

Darren Southwell, Adam Smart, Nicholas Macgregor, Samuel Merson

September 2021

The University of Melbourne

Australian Government
Parks Australia

A fig tree on Christmas Island. Image: Nicholas MacGregor

Cite this publication as: Southwell, D., Smart, A., Macgregor, N., Merson, S., 2021. Using power analysis and spatial prioritisation to optimise design of monitoring to detect population declines of forest birds on Christmas Island. NESP Threatened Species Recovery Hub Project 3.2.2.3, Report, Brisbane.

Cover image: The Christmas Island emerald dove (*Chalcophaps indica natalis*) is one of four forest bird species of concern on the island. Image: Margarita Goumas

Contents

Executive summary

Understanding statistical power of monitoring to detect changes in wildlife populations is essential for allocating monitoring effort and scarce conservation resources. Here, we evaluated the statistical power of monitoring to detect declines in occupancy of forest birds on Christmas Island, Australia. We fitted dynamic occupancy-detection models to repeat detection data collected over three seasons to estimate detection probabilities for four species of concern: Imperial pigeon (*Ducula whartoni*), Christmas Island white eye (*Zosterops natalis*), Christmas Island thrush (*Turdus poliocephalus erythropleurus*) and the Christmas Island emerald dove (*Chalcophaps indica natalis*). We combined detection estimates with species distribution models in a spatially explicit power analysis framework to quantify statistical power of alternative monitoring designs to detect plausible declines in occupancy over the next 10 years. We explored how the number of sites, the yearly interval between surveys, the number of repeat visits within a survey year (i.e. survey effort), and the placement of sites across the island influenced power. Across all species, power increased as the number of repeat visits increased, as the effect size increased, as the interval between surveys decreased, and when sites were targeted towards regions with the highest predicted occupancy. We found that power to detect declines in occupancy for three of the four species was high (>80%) for most monitoring design scenarios, except for when the number of sites dropped to 60 or when populations declined by 10%. Power was relatively low for the Emerald dove for almost all scenarios due to its relatively low occupancy and detectability. Our study demonstrates how data collected during the early stages of monitoring can be used to fine-tune design decisions so that monitoring has the greatest chance at meeting its objectives.

The Christmas Island thrush (*Turdus poliocephalus erythropleurus*) is one of four forest bird species of concern on the island.
Image: Margarita Goumas

Introduction

Monitoring the status and trends of plant and animal populations is crucial for determining whether populations are changing over time (Gerber et al. 1999); assessing whether management strategies are working (Holling 1978); tailoring management to the current state of a population, and/or; raising awareness and political support (Possingham et al. 2012). However, knowing how much to invest in monitoring, and where, when and how to allocate monitoring effort is complex (Legge et al. 2018). Decision-makers must weigh up difficult trade-offs, such as: which species to monitor; which population metrics to track; the type(s) of sampling methods; the duration of monitoring; the number and location of sites, and; the frequency and intensity of sampling. While there are many examples of well-funded and designed biodiversity monitoring programs, recent reviews of existing monitoring programs highlight that many are not adequately designed to detect meaningful population trends (Legge et al. 2018).

To be effective, monitoring needs to have clearly articulated objectives defined early in the design or evaluation process that clearly link back to management (Lindenmayer and Likens 2009). The choice of species to monitor should adequately represent threats, taxonomic groups, and ecological characteristics of the target region, as well as being sensitive to management interventions. Further, monitoring needs to be adequately designed to account for biases that may arise during sampling, such as imperfect detection (Guillera-Arroita and Lahoz-Monfort 2012). Such design challenges can be compounded by biological complexities of ecological systems, how rare or cryptic a species may be, the social context, and financial and logistical constraints (Field et al. 2005, Barata et al. 2017).

If the goal of monitoring is to detect a change in a state variable of interest, then monitoring should be designed to have sufficient statistical power. Statistical power analysis is a useful tool for designing and evaluating biological monitoring programs (Thomas and Juanes 1996), as it can assess ahead of time the chance that monitoring will detect changes in a population. Alternatively, it can assess the amount of effort needed to detect pre-specified effect sizes (for example, a 30% decline in a population). Power analysis is also useful when re-evaluating biodiversity monitoring programs because initial data can be analysed to refine monitoring design decisions and improve the allocation of scarce monitoring resources. Recent advancements allow power analysis to be spatially explicit, which allows heterogeneity in abundance/occupancy to be modelled (Ellis et al. 2014, Latif et al. 2017), and the effect of spatial location of monitoring sites on power to be assessed (Southwell et al. 2019). Despite these benefits, power analyses are rarely conducted during the design or evaluation stage of monitoring programs, which means that managers often have poorly informed expectations of how well a program is likely to perform (Wintle 2018).

In this report, we evaluated the statistical power of a biodiversity monitoring program on Christmas Island, an external territory of Australia and a site of international conservation significance. The small oceanic island (135 km^2), located only 300 kilometres from Indonesia, supports many threatened taxa, has a high proportion of endemic species, provides internationally significant seabird breeding habitat and is unique for its land crabs. Christmas Island biota are faced with a range of threatening processes, including invasive species and habitat disturbance and/or loss. The island has been the focus of several long-running and intensive biodiversity monitoring programs, including a large island-wide multi-species monitoring program, however, there is opportunity to evaluate alternative monitoring designs to ensure that resources are targeted most effectively towards detecting trends in priority species. Given limited resources are available for monitoring, identifying the most cost-effective allocation of funds is of paramount importance.

One group of species on the island that could benefit from an evaluation of monitoring protocols is the forest bird assemblage. To inform the design of a possible future forest bird survey program, we evaluated the statistical power of alternative monitoring design scenarios to detect declines in forest bird occupancy over time. First, we collated species distribution models for forest birds; second, we estimated detectability of forest birds by fitting dynamic occupancy-detection models to multi-year repeat-detection data. Third, we ranked existing monitoring sites and parts of the landscape yet to be monitored by their biodiversity value using the spatial prioritisation tool Zonation. Fourth, we calculated the statistical power of alternative monitoring designs to detect plausible declines in species occupancy. Finally, we explored trade-offs between the number of sites, the yearly interval between surveys and the number of repeat visits to a site on power. Our analysis will help understand the temporal variability in species occupancy, quantify how hard species are to detect during surveys, evaluate the chance of monitoring to detect future declines, and explore how monitoring could be more cost-effective, which is essential for effective biodiversity monitoring.

Methodology

Study site and species

Our study area comprised the entirety of Christmas Island (135,000 hectares), an Australian territory located south of Java in the Indian Ocean. Christmas Island is a site of international conservation significance. The island supports 32 taxa that are threatened under the *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act), including 19 terrestrial species (plants and animals), 13 marine species, and many others that are protected under international agreements. The island receives around 2000 millimetres of rainfall per year, supporting a mix of tropical rainforest and semideciduous rainforest, and two Ramsar-listed wetlands. A large proportion (c. 63%) of Christmas Island is protected by a National Park.

Long-term monitoring

Several intensive monitoring programs have targeted forest birds on Christmas Island. A pilot survey of forest birds was conducted at 128 sites in 2005 and early 2006 (James and Retallick 2007). In these surveys, sites were located at approximately 500 metre intervals along road and access tracks for ease of access and future repeatability. At each site a point count (hereafter referred to as a point-survey) was conducted for a fixed 10-minute period. All bird species detected either visually or audibly within the search radius (including those flying overhead) were recorded as present; those not detected were assumed absent. Sites were surveyed four times each (except for one site that was surveyed only three times), in February 2005, May-June 2005, September 2005 and January 2006. Each round of surveys was completed in 7 to 13 days. Surveys were undertaken only between 0600 to 1200 hours.

In addition, an island-wide survey was conducted at approximately 1000 sites every two years from 2001 to 2017. Sites were arranged in a regular grid across the island, approximately 400 metres apart. Although yellow crazy ants were the focus of the survey, other species including forest birds were surveyed in some years. At each site a 5-minute point-survey was conducted with bird species recorded visually or audibly. Following the point-survey, birds were also detected opportunistically while walking a 50 x 2 metre transect to survey for other species. Within each of these years, a random set of approximately 50 sites were surveyed twice and 25 were surveyed three times, with a small number surveyed four times. Repeat surveys generally occurred within a one to two weeks of one another.

Data collection

Species distribution models

We focused our analysis on four forest birds of conservation concern: Imperial pigeon (*Ducula whartoni*), Christmas Island white eye (*Zosterops natalis*), Christmas Island thrush (*Turdus poliocephalus erythropleurus*) and the Christmas Island emerald dove (*Chalcophaps indica natalis*). We obtained species distribution models (SDMs) for these species from Selwood et al. (2019) (Figure 1). The SDMs predict the probability of occupancy and were developed with presence-absence data from the island wide survey using boosted regression trees. Environmental predictors used in the models included: vegetation structure (canopy height, variation in canopy height), geology, topography (slope, elevation, aspect, topographic wetness index) and landscape context (distance to nearest valley, distance to nearest coast, distance to cleared areas). Further information about the modelling approach can be found in Selwood et al. (2019).

Repeat detection data

We estimated the probability of detecting each species during one unit of effort (i.e. the combined 5-minute fixed count and 50 metre line-transect survey) during the island wide survey. To separately estimate detection probability, it is necessary to have replicated observations from at least some monitoring sites (MacKenzie et al. 2002). Replicates can be collected by multiple independent observers, temporally replicated, or by spatial subsampling of a site (Mackenzie and Royle 2005). We extracted bird occurrence data from the island-wide survey data in the years 2011, 2013 and 2015 and generated detection histories for forest birds observed at least once during a survey: a 1 represented the detection of a species, a 0 represented a non-detection. Given a subset of sites was re-surveyed at least twice each year, often just a few weeks apart, we treated the temporal replication as repeat visits.

Dynamic occupancy-detection modelling

We fitted multi-season dynamic occupancy models to species' detection histories. This assumed any given survey was the result of two binomial processes (MacKenzie et al. 2002); the first, being the probability a species was present at a site (ψ); and the second, the probability a species was observed in any given survey visit given it was present (ρ). Occurrence at site i in the first year assumes a Bernoulli trial given by the occupancy probability in year one λ_{i1}:

$$z_{i1} = Bernoulli\ (\psi_{i1}) \tag{1}$$

For all subsequent years (t = 2, 3, ….,T), occurrence is a function of occurrence at site i at time t-1 and the probability of persistence and colonisation, respectively, given by:

$$z_{i1} = Bernoulli\ (z_{i,t-1}\ \varnothing_{it} + (1-z_{i,t-1})\ \gamma_{it}) \tag{2}$$

where ψ is the probability of occupancy at site I, z_i denotes the true state of occurrence and z_i is detection probability. The detection/non-detection data y_{ij} observed at site i during survey j can be described as:

$$y_{ijt} = Bernoulli\ (z_{it}\ p_{ijt}) \tag{3}$$

where y_{ij} is the observed 'presence-absence' data and ρ_{ij} is the probability of detection.

We fitted occupancy-detection models using the *colext* function in the *unmarked* package (Fiske and Chandler 2011) in the software R (R Development Core Team 2014). Occupancy-detection modelling generally assumes a closed population; that is, the home range of target species are smaller than a site. However, the home range of forest birds will be much larger than the area 'searched' during a point-survey. This means that occupancy in this case is better interpreted as site 'usage' (Kéry and Royle 2016).

Given our primary aim was to estimate detectability and not drivers of occupancy (because we already had SDMs), we fitted a single model to each species with occupancy and detectability held constant. We checked for model convergence and whether the output was likely to contain unrealistic estimates of occupancy or detectability where they unrealistically approached either 0 or 1, known as boundary estimates (Guillera-Arroita et al. 2010). We tested the goodness-of-fit by calculating the Mackenzie-Bailey chi-squared test using the *mb.gof.test* function in the *AICcmodavg* package (Mazerolle 2019). We used the predict function in the *Unmarked* package to obtain predictions of single-visit detection probability for each species.

Spatial prioritisation

We identified high priority regions for new surveys on Christmas Island using the spatial prioritisation tool Zonation (Lehtomaki and Moilanen 2013). Zonation evaluates the biodiversity value of all cells simultaneously for all components to develop a hierarchical (0–100%) ranking of a region. The top ranked areas maximise the representation of suitable habitat for all biodiversity components. We ran Zonation using the SDMs as biodiversity features and by applying the 'core area' function with a warp factor of 100 (the number of cells removed each iteration). The 'core area' function removes cells to ensure adequate representation across all species, rather than, for example, ranking cells by species richness.

Zonation can make use of a mask layer which determines the removal hierarchy of the cells in the analysis. This masking layer takes the form of a raster file that is of the same extent and projection as the input SDMs. When using a mask layer cells with a high mask level (a value of 1) are removed last as there may be a priori reasons for including them in the set of areas selected. These highly valued areas are included in the final solution regardless of their interaction with the biodiversity features. For example, studies to identify potential areas for conservation reserves commonly use a mask layer to lock in existing protected area networks.

On the assumption that the 128 site network from the original bird survey in 2005/2006 would provide a good foundation for a future survey design (as a widespread and accessible network across the island), we created a 100 metre buffer around these sites and assigned these areas a high mask value in the Zonation analysis. This ensured that other cells in the landscape were ranked to complement this existing site network, covering as efficiently as possible areas of suitable habitat for the four forest birds that were poorly represented (Figure 1). Comparing this solution with a solution with no mask layer present allowed us to rank the existing 128 sites by their underlying Zonation value for the purpose of exploring alternative monitoring designs based on a ranked subset of the original 128 sites. For example, with the 60 site scenario we included only the top 60 ranked sites from the existing network based on their Zonation ranking.

Spatially explicit power analysis

We used a spatially explicit simulation tool developed by Southwell et al. (2019) to estimate the statistical power of alternative monitoring designs at detecting future occupancy trends in forest birds. The tool runs in R (R Development Core Team 2014) and requires occupancy raster layers as a starting point for simulating likely trends in occupancy (either increasing or decreasing) over a monitoring horizon. Users specify species-specific estimates of detection probabilities for a given sampling method(s), the direction and magnitude (i.e. the effect size) of likely occupancy trends, and the location, frequency (i.e. survey years) and duration of surveys (i.e. number of days).

Using these inputs, the tool simulates likely detection histories for target species as the result of two binomial processes: whether a species is present or not at a site, given by the probability of occupancy, and if present, whether it is detected or not, given by the probability of detection and the number of repeated visits. Detection histories are simulated n times; statistical power is calculated as the proportion of those times that the modelled trend in occupancy is detected from the simulated datasets. A more detailed description of the simulation framework can be found in Southwell et al. (2019).

Monitoring design scenarios

We used the SDMs developed by Selwood et al. (2019) and the single-visit detection probabilities estimated above to initiate simulations. We simulated a range of monitoring design scenarios. In Scenario 1, we selected sites randomly from the existing 128 sites. If the number of sites in the scenario was greater than 128, we selected the remainder of sites from the top 10% of cells ranked by Zonation. In Scenario 2, we selected the existing 128 sites for survey in order of their Zonation ranking. If the number of sites in the scenario was greater than 128, we once again selected the remainder of sites from the top 10% of cells ranked by Zonation.

In Scenarios 1 and 2, we varied the number of sites (60, 128, 300, 500), the number of within year repeats (1, 2, 4 surveys), and the survey frequency (every 1, 2 and 4 years). For each scenario and design, we tested power to detect decreasing trends in species occupancy over a 10-year time horizon, ranging from 10 – 90% of current levels. In all cases, we ran 1000 simulations (n) for each scenario, species and effect size and conducted a one-tailed test with a type I error rate of α=0.1 to calculate power.

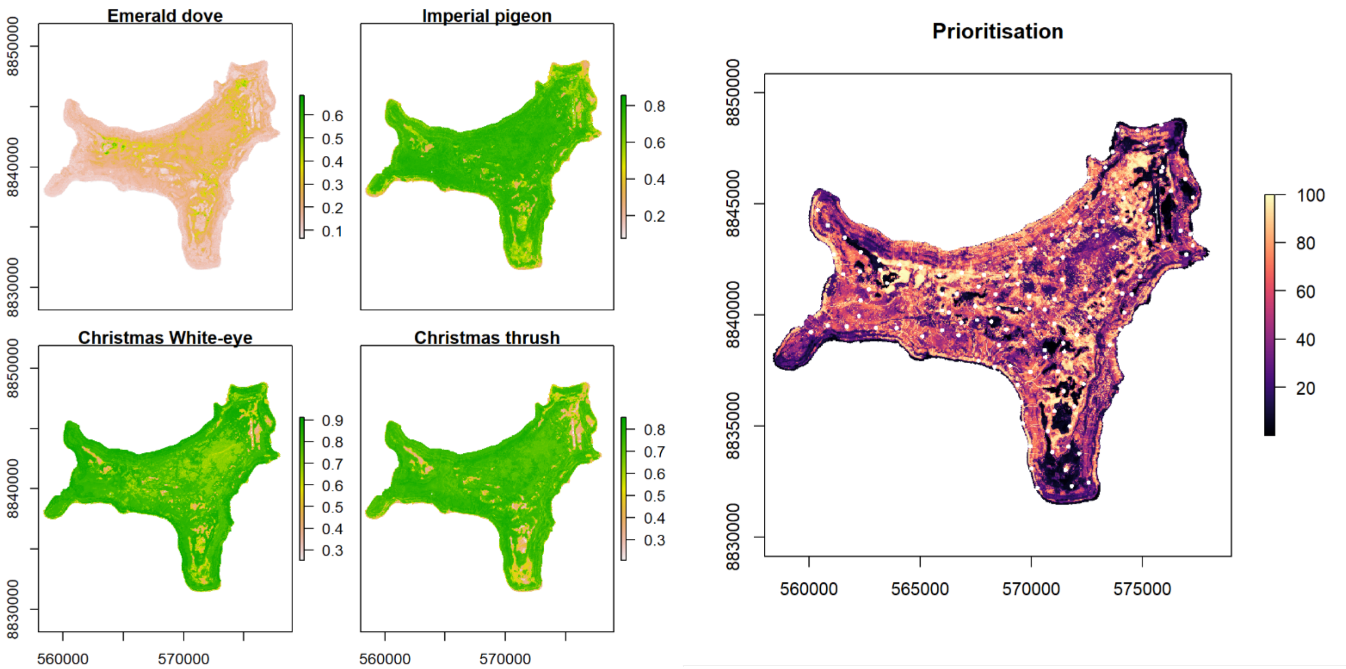


Figure 1: Species distribution models for the Emerald dove (*Chalcophaps indica natalis*), Imperial pigeon (*Ducula whartoni*), Christmas Island white eye (*Zosterops natalis*) and Christmas Island thrush (*Turdus poliocephalus erythropleurus*) obtained from Selwood et al. (2019), with green representing highest predicted occupancy. The panel on the right shows the results of the spatial prioritisation using Zonation, with yellow representing the highest ranked cells for new surveys. The white circles represent areas of the landscape that have been masked out of the zonation analysis (i.e. existing bird survey sites).

Results

Across the three survey years (2011, 2013 and 2015), there were 9022 detections of forest birds across four species: the Emerald dove was detected on 404 occasions; the Imperial pigeon on 2873 occasions; the Christmas Island white-eye on 2970 occasions; and the Christmas Island thrush on 2758 occasions. Our dynamic occupancy-detection modelling suggested the Christmas Island thrush and Imperial pigeon were most detectable, with single-visit detection probabilities of 0.91. The Christmas Island White-eye had a single visit detection probability of 0.83, while the Emerald dove had the lowest single detection probability of the four species (0.15).

Across all scenarios, power increased as the number of sites increased, as the number of repeat surveys within a given year increased, as the interval between survey years decreased, and when the decline in occupancy (i.e. the effect size) increased (Figure 1, 2). There were generally large increases in power between 10% and 30% declines. For example, when 128 existing sites were surveyed twice a year, every 2 years, power to detect 10% declines was 0.11 for the dove, 0.11 for the pigeon, 0.09 for the white-eye and 0.11 for the thrush. This increased to 0.12 for the dove, 0.58, 0.67 and 0.57, respectively, if the simulated decline in each species was 30%.

Generally, we found that power to detect declines in occupancy for three of the four species (pigeon, white-eye and thrush) was high (>80%) for most monitoring design scenarios, except for many cases in which the decline in occupancy was set at 10%, the number of sites surveyed dropped to 60, or sites were selected at random. In the case when only 60 sites were surveyed, there were no scenarios where 10% declines in any species could be detected with >80% power. With that number of sites, moderate declines of 30% could be detected for the three species with >80% power, but only when sites were targeted towards the cells prioritised by Zonation. Power to detect declines in the emerald dove was relatively low for most scenarios, except for when the number of sites exceeded 300, but even then, declines had to be moderate-to-large to achieve >80% power.

There was a large increase in power for all four species when the cells ranked highest by Zonation were prioritised for monitoring. For the pigeon, white-eye and thrush, in particular, power to detect 30% declines with 60 or 128 sites increased markedly when sites were prioritised. Not surprisingly, power was highest when 500 prioritised sites were surveyed. For example, power to detect 10% declines in the dove, pigeon, white-eye and thrush was 0.19, 0.87, 0.97 and 0.89 when 500 prioritised sites were surveyed four times per year.

The Christmas Island white-eye (*Zosterops natalis)* is one of four forest bird species of concern on the island.
Image: Margarita Goumas

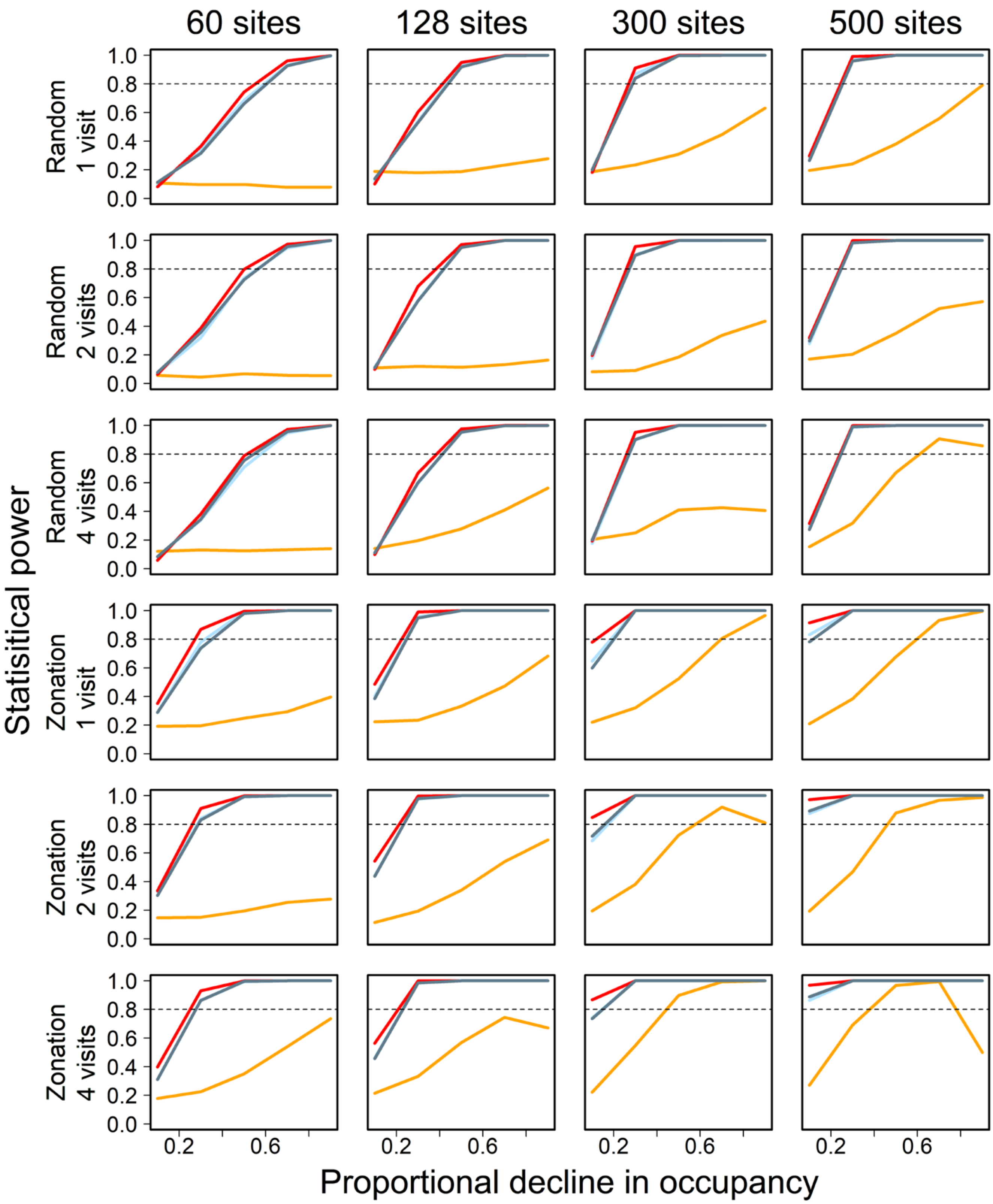


Figure 2: Statistical power (y-axis) to detect declines in occupancy (x-axis) for four forest birds on Christmas Island; Imperial pigeon (red line), Christmas Island white eye (light blue line), Christmas Island thrush (dark blue line) and the Christmas Island emerald dove (orange line). Columns represent scenarios where the number of sites is varied, rows represent scenarios where the number of repeat visits is varied. The top three rows represent scenarios where sites are selected at random, the bottom top three rows are scenarios where sites are prioritised using Zonation. All scenarios assume sites are surveyed every 2 years.

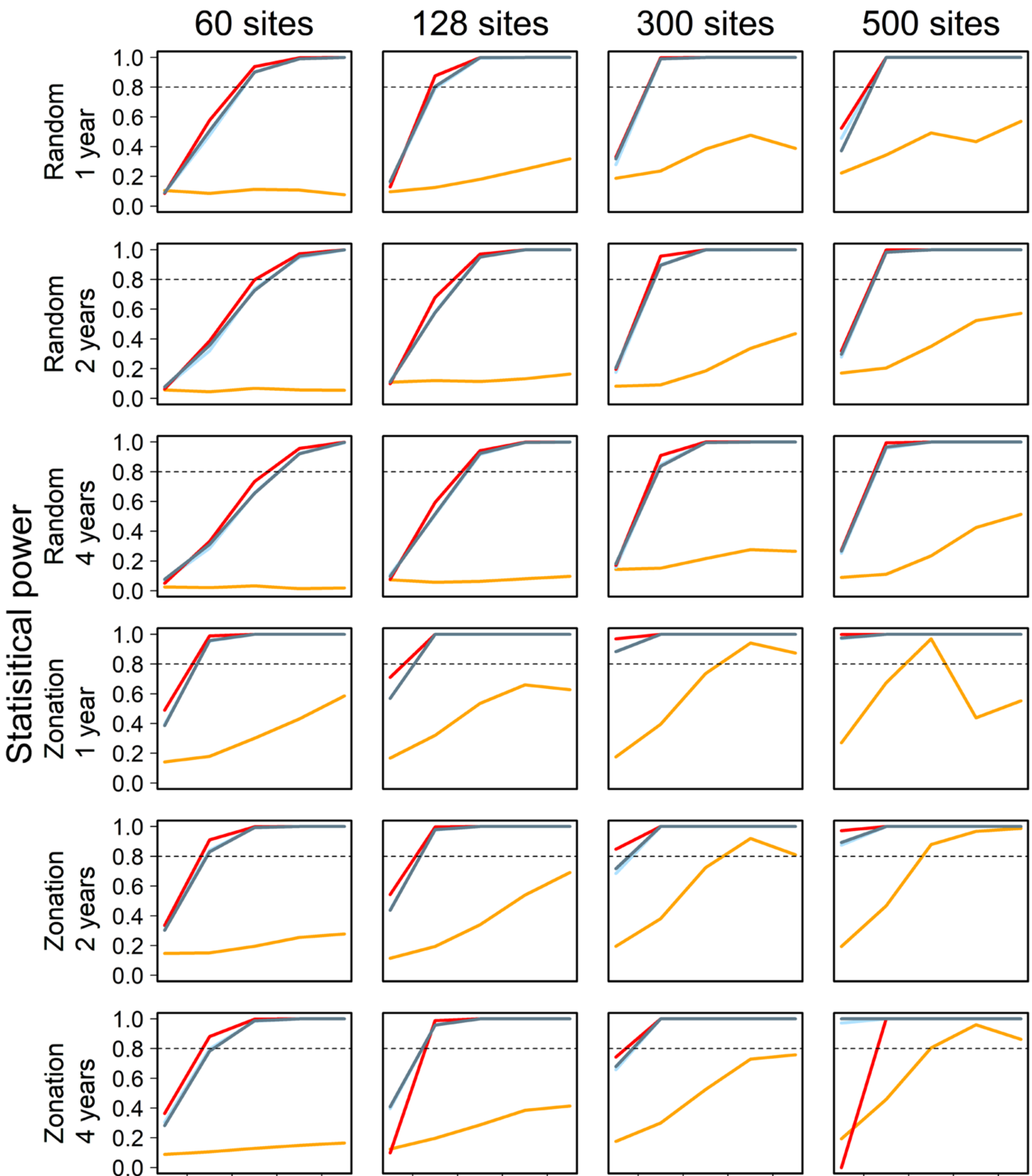


Figure 3: Statistical power (y-axis) to detect declines in occupancy (x-axis) for four forest birds on Christmas Island; Imperial pigeon (red line), Christmas Island white eye (light blue line), Christmas Island thrush (dark blue line) and the Christmas Island emerald dove (orange line). Columns represent scenarios where the number of sites is varied, rows represent scenarios where the yearly interval between surveys is varied. The top three rows represent scenarios where sites are selected at random, the bottom top three rows are scenarios where sites are prioritised using Zonation. All scenarios assume sites are visited twice on each survey year.

Discussion

Although statistical power is widely acknowledged as being important in the conservation and ecology literature, it is rarely considered during the design or evaluation phase of biodiversity monitoring (Ellis et al. 2015). In this study, we: 1) fitted dynamic occupancy-detection models to three seasons of occurrence data for four forest birds on Christmas Island; 2) identified regions across the island of highest predicted occupancy using species distribution models in Zonation; 3) modelled potential declines in the distribution of these species, and; 4) simulated alternative monitoring designs and calculated the statistical power to detect the modelled declines. Many studies have used spatial prioritisation tools to optimise survey locations (Amorim et al. 2014, Moran-Ordonez et al. 2018) or used statistical methods to determine the number of sites needed to detect population change (Steenweg et al. 2016, Southwell et al. 2019); however, to our knowledge few studies have combined these components into a single monitoring design framework. Such analyses are critical for evaluating the most cost-effective allocation of conservation resources and ensure that monitoring objectives are achieved.

Power to detect declines

Our results demonstrate that power to detect occupancy trends is highly sensitive to the number of sites surveyed and the magnitude of decline. Our simulations suggest that conducting 2 repeat surveys at 128 of the existing monitoring sites every 2 years could not detect 10% declines in any of the four species over the next 10 years with at least 80% power. However, power increased drastically as the magnitude of the simulated decline increased, especially from 10% to 30%. For example, simulated surveys of three of the four species had >80% power to detect a 30% decline when as few as 60 existing sites were monitored. The island-wide survey has traditionally surveyed the island very intensively, with sometimes up to 1000 sites visited in a given year. Our analysis suggests that, if the focus is primarily on detecting changes in the pigeon, white-eye and thrush, the 128-site network can have a high chance at detecting even small declines (10-30%). Power to detect declines in the emerald dove were consistently lower than the three other species. This is because it had relatively low levels of occupancy and detectability across the island, which meant that cells rarely became occupied during the simulations and, if they did, the species was difficult to detect. Increasing the number of existing sites monitored to 300 and 500 increased the chance of detecting 30% declines in this species. Similarly, increasing the number of visits to a site within a year from two to four increased power for the Emerald Dove.

Increasing the number of sites visits (i.e. repeat surveys within a survey year) increased power to detect declines in occupancy in all species, but to a much lower extent than increasing the number of sites or selecting sites using spatial prioritisation. This is likely because single visit detection probability was found to be high (~0.8-0.9) for three of the four species, which meant that there was only a relatively small marginal benefit from maximising the number of repeats. The exception was the Emerald Dove which, as mentioned above, had a much lower single-visit detection probability (0.15). Although the value of repeatedly surveying sites was relatively small for most species, we still believe that sites, or a subset of sites, should be surveyed twice a year (temporally), or separately by independent observers, so that detectability can be explicitly accounted for when estimating occupancy trends (MacKenzie et al. 2002). This is particularly important if detectability changes over time; if not accounted for, this would give the false impression that populations are changing when in fact they may not be. We could not find any rules of thumb in the literature on the minimum number of sites that must be re-surveyed in an occupancy-detection analysis as this is likely to depend on a number of factors, such as true occupancy, detectability and the number of sites.

An important consideration in any monitoring program is the survey frequency (i.e. the yearly interval between surveys). Not surprisingly, we found that surveying less frequently reduced power when a constant number of sites were surveyed on each occasion. This may not always be the case: power may increase with a long interval between surveys if the number of sites surveyed on each occasion increases; however, this depends critically on the relationship between number of sites and frequency (Einoder et al. 2018). The most appropriate survey frequency will also depend on additional factors not considered here, such as resource and logistical constraints; the status of target species (i.e. it might be more important to monitor threatened species with small populations more frequently); generation length of target species, and how tolerant managers are to risk. A risk averse manager might prefer short intervals between surveys for species with a high chance of decline in the interim. It is crucial that managers consider these trade-offs when justifying the costs associated with monitoring.

By conducting a spatial prioritisation in Zonation, we evaluated power with sites targeted towards regions of highest predicted occupancy while ensuring representation across species. This, along with the number of sites, resulted in the largest gains in power compared to variations in the survey frequency or number of repeats. This component of our analysis demonstrates how the location of sites relative to the distribution of species influences power and highlights the need for managers to clearly identify the target species and have a good understanding of their likely distribution when designing a monitoring program. If this is not possible, species distributions can be modelled during the re-evaluation stage of a monitoring program when initial data has been collected, as was done here. To our knowledge, there are few examples where gains in power due to the placement of sites in a landscape relative to the distribution of species has been quantified.

Assumptions and future research priorities

Our approach was subject to a number of limitations and assumptions. First, we used existing SDMs to predict current occupancy of target species. We could have built our own SDMs that accounted for detectability, however, we decided against this given occupancy was already very high for three of the four species. Secondly, we simulated linear declines in occupancy over time across a range of plausible effect sizes. Our approach could be extended to include more complicated temporal and spatial range dynamics, such as contractions, expansions or shifts over space and/or no-linear declines over time. Finally, we modelled trends in occupancy rather than trends in abundance over time. We therefore assumed a 1:1 relationship between occupancy and abundance (Stanley and Royle 2005), meaning that all occupied cells declined in the same way regardless of how many individuals were within them. Abundance data were not available from monitoring sites for our target species. Our approach could be extended in future to estimate power to detect trends in abundance or density, rather than just occupancy. Power to detect changes in abundance would likely be higher than occupancy, but may come at the cost of increased sampling expenses.

Conclusion

Small to moderate declines in occupancy for three of the four forest birds can be detected with much fewer sites than have been previous surveyed on Christmas Island. Monitoring approximately 128 sites will have >80% power for three of the four species assuming declines of at least 30%. Power to detect changes in the emerald dove was maximised by targeting a subset of new sites towards regions of highest predicted occupancy. We recommend that all sites, or at least a subset of sites, be surveyed twice per year so that data can be analysed in an occupancy-detection framework. Finally, all participants should be adequately trained to minimise false-positives and ensure consistent record keeping across participating monitoring groups. Our study demonstrates how data collected during the early stages of monitoring can be used to fine-tune design decisions so that monitoring can be implemented cost-effectively and with the greatest chance at meeting its objectives.

Acknowledgements

This research was funded by the National Environmental Science Programs (NESP) Threatened Species Recovery Hub. We are grateful to Tanya Detto, Kerrie Bennison and Brendan Tiernan at Christmas Island National Park for providing data and discussing the results.

The imperial pigeon (*Ducula whartonii*) is one of four forest bird species of concern on the island. Image: Margarita Goumas

References

Amorim, F., S. B. Carvalho, J. Honrado, and H. Rebelo. 2014. Designing Optimized Multi-Species Monitoring Networks to Detect Range Shifts Driven by Climate Change: A Case Study with Bats in the North of Portugal. *Plos One* 9.

Barata, I. M., R. A. Griffiths, and M. S. Ridout. 2017. The power of monitoring: optimizing survey designs to detect occupancy changes in a rare amphibian population. *Scientific Reports* 7.

Einoder, L., D. Southwell, J. Lahoz-Monfort, G. Gillespie, and B. Wintle. 2018. Optimising broad-scale monitoring for trend detection: review and re-design of a long-term program in northern Australia.in S. Legge, D. Lindenmayer, N. Robinson, B. Scheele, D. Southwell, and B. Wintle, editors. Monitoring Threatened Species and Ecological Communities. CSIRO Publishing Melbourne

Ellis, M. M., J. S. Ivan, and M. K. Schwartz. 2014. Spatially explicit power analyses for occupancy-based monitoring of wolverine in the U.S. Rocky Mountains. *Conservation Biology* 28:52-62.

Ellis, M. M., J. S. Ivan, J. M. Tucker, and M. K. Schwartz. 2015. rSPACE: Spatially based power analysis for conservation and ecology. *Methods in Ecology and Evolution* 6:621-625.

Field, S. A., A. J. Tyre, and H. P. Possingham. 2005. Optimizing allocation of monitoring effort under economic and observational constraints. *Journal of Wildlife Management* 69:473-482.

Fiske, I., and R. Chandler. 2011. unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance. *Journal of Statistical Software* 43:1-23.

Gerber, L. R., D. P. DeMaster, and P. M. Kareiva. 1999. Gray whales and the value of monitoring data in implementing the US Endangered Species Act. *Conservation Biology* 13:1215-1219.

Guillera-Arroita, G., and J. J. Lahoz-Monfort. 2012. Designing studies to detect difference in species occupancy: power analysis under imperfect detection. *Methods in Ecology and Evolution* 3:860-869.

Guillera-Arroita, G., M. S. Ridout, and B. J. T. Morgan. 2010. Design of occupancy studies with imperfect detection. *Methods in Ecology and Evolution* 1:131-139.

Holling, C. S. 1978. Adaptive environmental assessment and management. John Wiley and Sons, London, UK.

James, D. J., and K. Retallick. 2007. Forest Birds of Christmas Island: A Baseline Survey of Abundance. Parks Australia North Christmas Island Biodiversity Monitoring Programme:Report to the Department of Finance and Deregulation and the Department of the Environment, Water, Heritage and the Arts, Canberra.

Kéry, M., and J. A. Royle. 2016. Applied hierarchical modelling in ecology. Analysis of distribution, abundance and species richness in R and BUGS. Academic Press, Oxford.

Latif, Q. S., M. M. Ellis, V. A. Saab, and K. Mellen-McLean. 2017. Simulations inform design of regional occupancy-based monitoring for a sparsely distributed, territorial species. *Ecology and Evolution*.

Legge, S., D. Lindenmayer, N. Robinson, B. Scheele, D. Southwell, and B. Wintle. 2018. Monitoring threatened species and ecological communities. CSIRO, Clayton South, Victoria, Australia.

Lehtomaki, J., and A. Moilanen. 2013. Methods and workflow for spatial conservation prioritization using Zonation. *Environmental Modelling & Software* 47:128-137.

Lindenmayer, D. B., and G. E. Likens. 2009. Adaptive monitoring: a new paradigm for long-term research and monitoring. *Trends in Ecology & Evolution* 24:482-486.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royle, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. *Ecology* 83:2248-2255.

Mackenzie, D. I., and J. A. Royle. 2005. Designing occupancy studies: general advice and allocating survey effort. *Journal of Applied Ecology* 42:1105-1114.

Mazerolle, M. J. 2019. AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c). https://cran.r-project.org/package=AICcmodavg.

Moran-Ordonez, A., S. Canessa, G. Bota, L. Brotons, S. Herrando, and V. Hermoso. 2018. Efficiency of species survey networks can be improved by integrating different monitoring approaches in a spatial prioritization design. *Conservation Letters* 11.

Possingham, H. P., B. A. Wintle, R. A. Fuller, and L. N. Joseph. 2012. The Conservation return on investment from ecological monitoring. Pages 49-61 in D. B. Lindenmayer and P. Gibbons, editors. *Making Biodiversity Monitoring Happen in Australia*. CSIRO Publishing, Melbourne.

R Development Core Team. 2014. R: A language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria.

Selwood, K. E., B. A. Wintle, and H. Kujala. 2019. Collaborative conservation planning: Quantifying the contribution of expert engagement to identify spatial conservation priorities. *Conservation Letters* 12.

Southwell, D. M., L. D. Einoder, J. J. Lahoz-Monfort, A. Fisher, G. R. Gillespie, and B. A. Wintle. 2019. Spatially explicit power analysis for detecting occupancy trends for multiple species. *Ecological Applications* 29.

Stanley, T. R., and J. A. Royle. 2005. Estimating site occupancy and abundance using indirect detection indices. *Journal of Wildlife Management* 69:874-883.

Steenweg, R., J. Whittington, M. Hebblewhite, A. Forshner, B. Johnston, D. Petersen, B. Shepherd, and P. M. Lukacs. 2016. Camera-based occupancy monitoring at large scales: Power to detect trends in grizzly bears across the Canadian Rockies. *Biological Conservation* 201:192-200.

Thomas, L., and F. Juanes. 1996. The importance of statistical power analysis: An example from Animal Behaviour. *Animal Behaviour* 52:856-859.

Wintle, B. A. 2018. Why, what, how much, and is it worth it? Questions to answer before spending a penny on monitoring. Pages 211-216 in S. Legge, N. Robinson, D. Lindenmayer, B. Scheele, D. M. Southwell, and B. A. Wintle, editors. Monitoring Threatened Species and Ecological Communities. CSIRO Publishing, Clayton South, Australia.

Forest bird habitat on Christmas Island. Image: Margaria Goumas

Further information:

http://www.nespthreatenedspecies.edu.au

This project is supported through funding from the
Australian Government's National Environmental Science Program.

Threatened Species Recovery Hub

National Environmental Science Programme