Using power analysis and spatial prioritization to evaluate the design of a forest bird monitoring programme

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Abstract Biodiversity monitoring programmes should be designed with sufficient statistical power to detect population change. Here we evaluated the statistical power of monitoring to detect declines in the occupancy of forest birds on Christmas Island, Australia. We fitted zero-inflated binomial models to 3 years of repeat detection data (2011, 2013 and 2015) to estimate single-visit detection probabilities for four species of concern: the Christmas Island imperial pigeon *Ducula whartoni*, Christmas Island white-eye *Zosterops natalis*, Christmas Island thrush *Turdus poliocephalus erythropleurus* and Christmas Island emerald dove *Chalcophaps indica natalis*. We combined detection probabilities with maps of occupancy to simulate data collected over the next 10 years for alternative monitoring designs and for different declines in occupancy (10–50%). Specifically, we explored how the number of sites (60, 128, 300, 500), the interval between surveys (1–5 years), the number of repeat visits (2–4 visits) and the location of sites influenced power. Power was high (> 80%) for the imperial pigeon, white-eye and thrush for most scenarios, except for when only 60 sites were surveyed or a 10% decline in occupancy was simulated over 10 years. For the emerald dove, which is the rarest of the four species and has a patchy distribution, power was low in almost all scenarios tested. Prioritizing monitoring towards core habitat for this species only slightly improved power to detect declines. Our study demonstrates how data collected during the early stages of monitoring can be analysed in simulation tools to fine-tune future survey design decisions.

Keywords Christmas Island, detectability, forest birds, monitoring, occupancy models, simulation, statistical power, survey design

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Introduction

Biodiversity monitoring is important for determining the status of populations and how they are trending over time (Gerber et al., 1999). Monitoring also provides essential information for evaluating the effectiveness of management actions (Holling, 1978) and raising awareness or political support (Possingham et al., 2012). However, knowing how much to invest in monitoring, and where, when and how to allocate this effort across space and time is difficult (Legge et al., 2018). Practitioners are faced with a series of complex decisions about which species to monitor, what to measure, the type(s) of sampling methods to deploy, the duration of monitoring, the number and location of sites and the frequency and intensity of sampling. Although there are many examples of successful biodiversity monitoring programmes, recent reviews have shown that most are inadequately designed or resourced to achieve their objectives (Scheele et al., 2019; Lavery et al., 2021).

If the goal is to detect a change or trend in a state variable of interest (i.e. abundance or occupancy), then monitoring should be designed to have sufficient statistical power to detect that change (Steidl et al., 1997; Strayer, 1999). Statistical power is the chance of correctly rejecting the null hypothesis that no change has occurred in a state variable of interest, such as population size or occupancy (Thomas & Juanes, 1996). Power analysis is a critical component of monitoring design because it can assess the chance that monitoring will detect a change in a population (Thorn et al., 2011; Loos et al., 2015) or the level of effort (e.g. the number of sites or the time spent at sites) needed to detect a change with a desired level of confidence (Barata et al., 2017). Although many tools have been developed to assist practitioners in designing monitoring programmes (Wauchope et al., 2019), they are rarely utilized during the design phase of monitoring or to evaluate the performance of long-running biodiversity monitoring programmes.

Correlative species distribution models are routinely used in conservation planning to improve the coverage of protected areas (Elith & Leathwick, 2009; Carvalho et al., 2010); however, they can also be used to design cost-efficient monitoring networks (Amorim et al., 2014; Vicente et al., 2016). There are few studies that link species distribution models, spatial prioritization and power analysis in a single monitoring design framework (Ellis et al., 2014; Southwell et al., 2019; Smart et al., 2022). Spatially explicit power analysis

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is valuable for determining the optimal placement and number of sites within a landscape needed to detect change in the expected distributions of species (Ellis et al., 2014; Southwell et al., 2019). The approach is especially useful when target species are found at different locations or have fragmented distributions, resulting in significant variation in power between species for a given positioning of sites across a landscape (Smart et al., 2022; Southwell et al., 2022).

In this study, we combined species distribution modelling, detectability modelling, spatial prioritization and power analysis to evaluate the likely performance of biodiversity monitoring on Christmas Island, a small island in the Indian Ocean. The island has a high proportion of endemic species and supports many threatened taxa, making it a site of international conservation significance (Eldridge et al., 2014). Christmas Island biota are faced with a range of threats, including invasive species and habitat disturbance. As a result, the island has been the focus of several long-running and intensive biodiversity monitoring programmes, including a large island-wide multi-species monitoring programme (Abbott, 2006). The availability of data from those past programmes provides a valuable opportunity to evaluate alternative monitoring designs that could be implemented in future to ensure that resources are targeted most effectively towards detecting trends in priority species.

We focused on four forest birds of conservation concern on Christmas Island: the Christmas Island imperial pigeon *Ducula whartoni*, Christmas Island white-eye *Zosterops natalis*, Christmas Island thrush *Turdus poliocephalus erythropleurus* and Christmas Island emerald dove *Chalcophaps indica natalis*. We estimated detection probabilities for these species by fitting detection models to historic multi-year repeat detection data. We combined existing maps of the predicted habitat suitability for each species in a spatial prioritization tool, *Zonation* (Lehtomaki & Moilanen, 2013), to rank grid cells in the landscape for future surveys. We combined the occupancy maps and detection probabilities to simulate data that could be collected in future under various monitoring design scenarios and assumptions about how species decline. For each scenario we calculated the statistical power to detect declines depending on decisions about the number of sites, the interval between surveys and the number of repeat visits to a site. Our analysis will help inform how monitoring effort is allocated on Christmas Island in future and provides a general simulation framework for evaluating monitoring design.

Methods

Study area

Our study area comprised the entirety of Christmas Island (135,000 ha), an Australian territory located 300 km south of Java (Indonesia) in the Indian Ocean (Fig. 1). The island receives c. 2,000 mm of rainfall per year, supporting a mix of tall tropical rainforest and semi-deciduous rainforest on the plateau and semi-evergreen thickets on coastal terraces. A large proportion (c. 63%) of Christmas Island is protected by a national park, supporting rich and distinctive biota. Ecosystem dynamics are driven by abundant land crabs (most notably the Christmas Island red crab *Gecarcoidea natalis*), which regulate seedling recruitment and litter breakdown (Green et al., 1999).

Forest bird monitoring data

Several monitoring programmes have targeted the four forest bird species that are the focus of this study. During 2005–2006, a pilot survey for forest birds was conducted at 128 sites located at c. 500-m intervals along roads and tracks. These sites were chosen for ease of access and with future repeatability in mind (James & Retallick, 2007). At each site, a point survey was conducted for a fixed 10-min period. All bird species detected either visually or audibly at each point (including those flying overhead) were recorded as present; all others were recorded as not detected.

A more intensive island-wide biodiversity survey has also been conducted biannually during 2001–2021 at c. 1,000 sites positioned in a regular grid across the island (spaced 400 m apart). Although the purpose of this programme was primarily to monitor the abundance and activity of Christmas Island red crabs and invasive yellow crazy ants *Anoplolepis gracilipes*, forest birds were also recorded until 2015. At each site, a 5-min point-survey was conducted, with bird species recorded visually or auditorily, followed by opportunistic sightings whilst walking two 50-m transects to survey for other species (each starting in opposite directions from the point count).

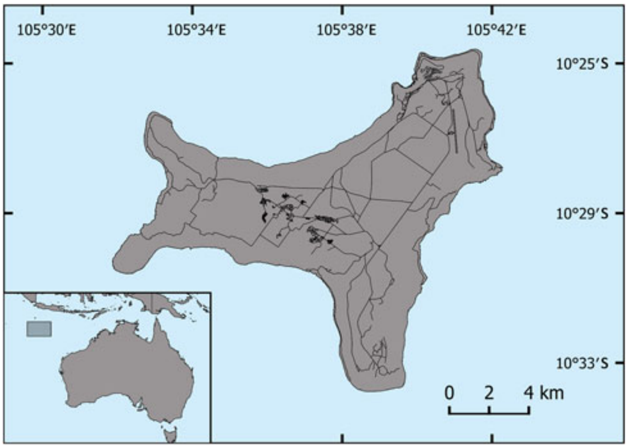

Fig. 1 Christmas Island, with the major road network (black lines). The inset map shows the location of Christmas Island with respect to Australia and Indonesia.

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During the island-wide survey, within-year repeat surveys were conducted in 2009, 2011, 2013 and 2015. In these years, a random subset of c. 50 sites were surveyed twice, 25 sites were surveyed three times and a smaller number were surveyed four times. Inspection of the data revealed that the median time between repeats was 7–8 days (except for surveys in 2009), which meant that repeat surveys were generally completed within 2–3 weeks. All surveys were conducted outside the birds' breeding season during May–October. From this, detection histories for forest birds observed at least once during a survey were constructed, with 1 representing the detection of a species and 0 representing non-detection.

Monitoring objective

We assumed that the primary objective of a targeted forest bird monitoring programme was to detect declines in occupancy of the four priority species over a 10-year time horizon. Given the accessibility of the 128 sites piloted during 2005–2006, we assumed that these sites formed the foundation of monitoring (hereafter referred to as 'core sites'). To evaluate alternative monitoring designs, we estimated single-visit detection probabilities, collated published maps of occupancy and simulated future monitoring data under assumptions about change. These steps are outlined in further detail below and illustrated in Fig. 2.

Single-visit detection probabilities

We calculated a mean single-visit detection probability for the four species by fitting a zero-inflated binomial model to island-wide survey data (Wintle et al., 2004, 2005). We only used data collected in 2011, 2013 and 2015 when the time between repeats was minimal (on average 7–8 days). When species are not perfectly detectable, site occupancy data are the realizations of two binomial processes acting simultaneously: (1) the probability of sites being occupied over a relatively long period, and (2) the probability of observing the species in any one visit to those sites. The outcome of these two processes over all survey sites is a finite mixture distribution known as the zero-inflated binomial mixture model, where the probability (PR) that the random variable Y takes a value of 0 or y is given by:

$$\begin{aligned} \mathrm{PR}[Y=0] &= 1-\Psi+\Psi(1-p)^{v} \\ \mathrm{PR}[Y=y] &= \Psi\binom{v}{y}p^{y}(1-p)^{v-y} \end{aligned} \tag{1}$$

where y is the number of detections in v visits to sites, Ψ is the probability of sites being occupied and p is the single-visit detection probability. We estimated the single visit detection probability using Markov chain Monte Carlo sampling in the *rjags* package in *R 4.2.0* (Plummer, 2003). We ran two parallel chains for 100,000 iterations with the burn-in set to 50,000 and thinning equal to 2. We assessed model convergence using the *CODA* package (Plummer et al., 2006) and ensured that R-hat values did not exceed 1.1 (Brooks & Gelman, 1998). We assigned vague normal priors to all model parameters $N(0, 10^{-6})$.

Species distribution models

We obtained published raster layers of the predicted occupancy of priority species on Christmas Island from Selwood et al. (2019; Fig. 3). These authors developed maps by fitting boosted regression trees to presence–absence data collected during the island-wide survey collapsed across 2001–2015. The maps predict the probability of occupancy on a 0–1

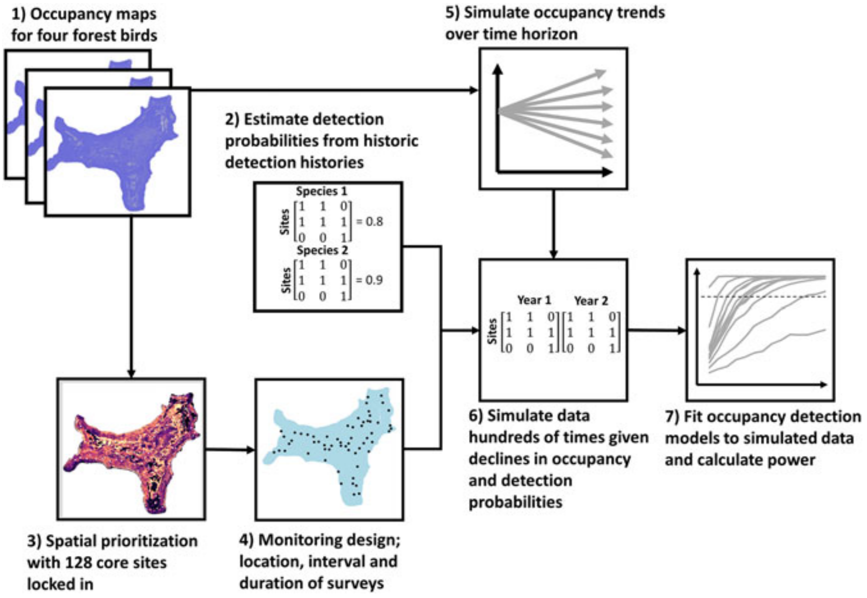

Fig. 2 Diagram of the spatially explicit power analysis that combines detectability modelling, species distribution modelling, spatial prioritization, data simulation and power analysis.

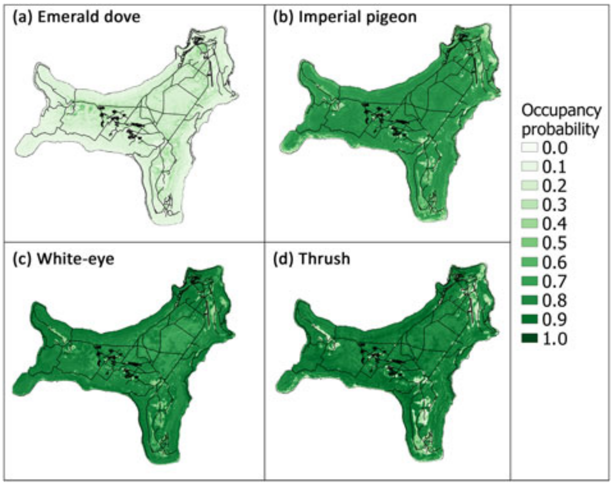

Fig. 3 Species distribution models for (a) the Christmas Island emerald dove *Chalcophaps indica natalis*, (b) the Christmas Island imperial pigeon *Ducula whartoni*, (c) the Christmas Island white-eye *Zosterops natalis* and (d) the Christmas Island thrush *Turdus poliocephalus erythropleurus* obtained from Selwood et al. (2019), with darker shades representing higher predicted occupancy.

scale with a 10-m resolution. The environmental predictors used in the boosted regression trees included vegetation structure (canopy height, variation in canopy height, vegetation type), 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 on the modelling and the relative importance of key predictor variables is presented in Supplementary Figs 1–4.

The imperial pigeon, white-eye and thrush are predicted to be widespread and common across the island, whereas the emerald dove is predicted to be relatively restricted in its range, with much lower probabilities of occupancy (Fig. 3). Importantly, the occupancy maps were developed in close consultation with experts (mainly national park practitioners) to inform future decisions concerning land use across the island. We therefore believe that they provide reliable predictions of the current distribution of the four forest birds. Further information about the modelling and refinement of models with experts can be found in Selwood et al. (2019).

Spatial prioritization

We input the occupancy raster layers described above into the spatial prioritization tool *Zonation* to identify cells most likely to contain the four priority species. *Zonation* runs by iteratively removing cells that cause the smallest marginal loss in the biodiversity value (e.g. abundance or occupancy probability) across biodiversity features (e.g. species; Lehtomaki & Moilanen, 2013). This generates a hierarchical ranking of cells across the landscape based on marginal loss. Cells with a value of 0 are the lowest priority, whereas those with a value of 1 are the highest priority. In this case, highest-priority cells maximized predicted occupancy across the four priority species whilst ensuring adequate representation of each species.

We ran *Zonation* using the *core area* function with a warp factor of 100, which is the number of cells removed at each iteration. The *core area* function removed cells to ensure adequate representation across all species rather than ranking cells by species richness. *Zonation* can lock in designated cells as the highest priority even if they have a small marginal loss. This may be done to expand an existing reserve or monitoring network as efficiently as possible, so that the highest-ranked cells best complement those that are already locked in. We ran *Zonation* with the 128 core sites locked in, including a 100-m buffer around each site to avoid placing new sites immediately adjacent to these. We weighted all four species equally in the *Zonation* analysis.

Monitoring design scenarios and data simulation

We explored a range of alternative monitoring design scenarios targeting the priority forest birds. In Scenario 1, we selected sites randomly across the island, ignoring the 128 core sites locked into the *Zonation* analysis. In Scenario 2, we selected the core sites first then additional sites across the island based on their *Zonation* ranking. In Scenario 3, we targeted only habitats where the probability of occupancy for the emerald dove exceeded 0.5. In each scenario, we varied the number of sites (60, 128, 300, 500), the number of within-year repeats (2–4 visits) and the number of years between surveys (survey frequency of once every 1–5 years).

For each scenario and monitoring design, we simulated detection histories that could be collected in future assuming plausible declines in occupancy. We simulated a linear decline in occupancy of cell j for species s over time t, given by Equation 2:

$$\Psi_{t,s} = \Psi_{0,s}\left(1 - \left(\frac{E}{T_{max}}\right)t\right) \qquad (2)$$

where E is the effect size, T_{max} is the length of the monitoring programme and s is the species. We tested a range of plausible effect sizes over a 10-year time horizon (T_{max}) ranging from 10–50% declines in initial starting occupancy.

We simulated detection/non-detection data for each monitoring scenario. To determine the occupancy state of cell j at time t, we conducted a Bernoulli trial, with the probability of success equal to the occupancy probability of that cell at time t. We assigned an occupancy state of 1 to cells where species s was deemed present, otherwise cells were given a value of 0 (absent). For each species, we simulated detection histories for k repeat visits to monitoring sites by conducting a second

Bernoulli trial, with the probability of success equal to the single-visit detection probabilities estimated above.

Spatial power analysis

For each species, we calculated the statistical power of the alternative monitoring designs at detecting the simulated declines in occupancy. To calculate statistical power, we fitted an occupancy detection model to the simulated detection histories using the *unmarked* package in *R* (Kellner et al., 2022) according to Equation 3:

$$\text{logit}(\Psi_{t,s}) = \alpha_0 + \alpha_1 \times \text{year} \tag{3}$$

where Ψ is occupancy in year t for species s, α_0 is the intercept and α_1 is the trend parameter. We simulated detection histories 500 times for each species and scenario. We calculated statistical power as the proportion of those times that the trend parameter α_1 estimated from the simulated data was statistically significant. We conducted a one-tailed test with a type I error rate of $\alpha = 0.05$. A more detailed description of the power analysis framework can be found in Southwell et al. (2019).

Results

Single-visit detection probability

Across the years in which replicate surveys were conducted (2011, 2013, 2015), there were 13,198 detections of the four forest bird species. The emerald dove was detected on 861 occasions, the imperial pigeon on 3,067 occasions, the white-eye on 4,345 occasions and the thrush on 4,925 occasions. Our single-visit detection model suggested that the imperial pigeon (0.873; 95% CI: 0.859–0.897) and the white-eye (0.904; 95% CI: 0.893–0.913) had the highest single-visit detection probabilities during one 5-min point count survey, followed by the thrush (0.839; 95% CI: 0.827–0.851). The emerald dove had the lowest single-visit detection probability of the four species (0.122; 95% CI: 0.109–0.136; Table 1).

Table 1 Detectability estimates for the Christmas Island emerald dove *Chalcophaps indica natalis*, Christmas Island imperial pigeon *Ducula whartoni*, Christmas Island white-eye *Zosterops natalis* and Christmas Island thrush *Turdus poliocephalus erythropleurus* during 5-min fixed counts and 50-m line-transect surveys in the study area (Fig. 1).

Species	Single-visit detection probability (95% CI)
Emerald dove	0.122 (0.109–0.136)
Imperial pigeon	0.873 (0.859–0.897)
White-eye	0.904 (0.893–0.913)
Thrush	0.839 (0.827–0.851)

Statistical power

Across all monitoring design scenarios, power increased as the number of sites increased, as the number of repeat surveys increased, as the interval between survey years decreased and when the decline in occupancy (i.e. the effect size) increased (Figs 4–6). Power to detect declines in the imperial pigeon, white-eye and thrush was relatively high for most scenarios; there was generally at least an 80% chance at detecting 30–50% declines over the 10-year monitoring horizon when 60 or 128 sites were surveyed, whereas surveying 300 or 500 sites resulted in $> 80\%$ power even for 10% declines in occupancy. By contrast, power to detect declines in the emerald dove was relatively low. Power exceeded 80% only in cases when 300–500 sites were monitored and declines of 40–50% were assumed.

There was relatively little gain in power as the number of repeat visits increased from two to four, especially for the imperial pigeon, white-eye and thrush. For example, power to detect 10% declines in the thrush with 128 sites increased from 0.276 to 0.308 when the number of repeat visits to sites surveyed every second year increased from two to four. Increasing the number of visits for the emerald dove also had relatively little positive effect on power compared to increasing the number of sites. For all species, power decreased as the interval between surveys increased from 1 year to 5 years. For example, power to detect 30% declines of the imperial pigeon decreased from 0.892 to 0.661 when the monitoring frequency reduced from annually to every 5 years, assuming 128 sites were surveyed on each occasion, with two repeat visits. However, changes in the monitoring frequency did not influence power as much as changes to the number of sites.

Spatial prioritization

The spatial prioritization ranked cells across Christmas Island by their predicted occupancy whilst accounting for equal representation of species. Because three of the four species were widespread, the highest-ranked cells closely matched the predicted distribution of the emerald dove (Fig. 7). There was little difference in power for the imperial pigeon, white-eye and thrush when monitoring was targeted towards sites ranked highly by *Zonation* compared to randomly selected sites. In contrast, there was a small gain in power for the emerald dove when monitoring sites were prioritized with *Zonation*, and there was a further gain when sites specifically targeted the most suitable emerald dove habitat. For example, power to detect 50% declines in occupancy with 300 sites was 0.32 when sites were selected at random, 0.45 when sites were prioritized with *Zonation* and 0.71 when all sites targeted the most suitable emerald dove habitat (Fig. 6).

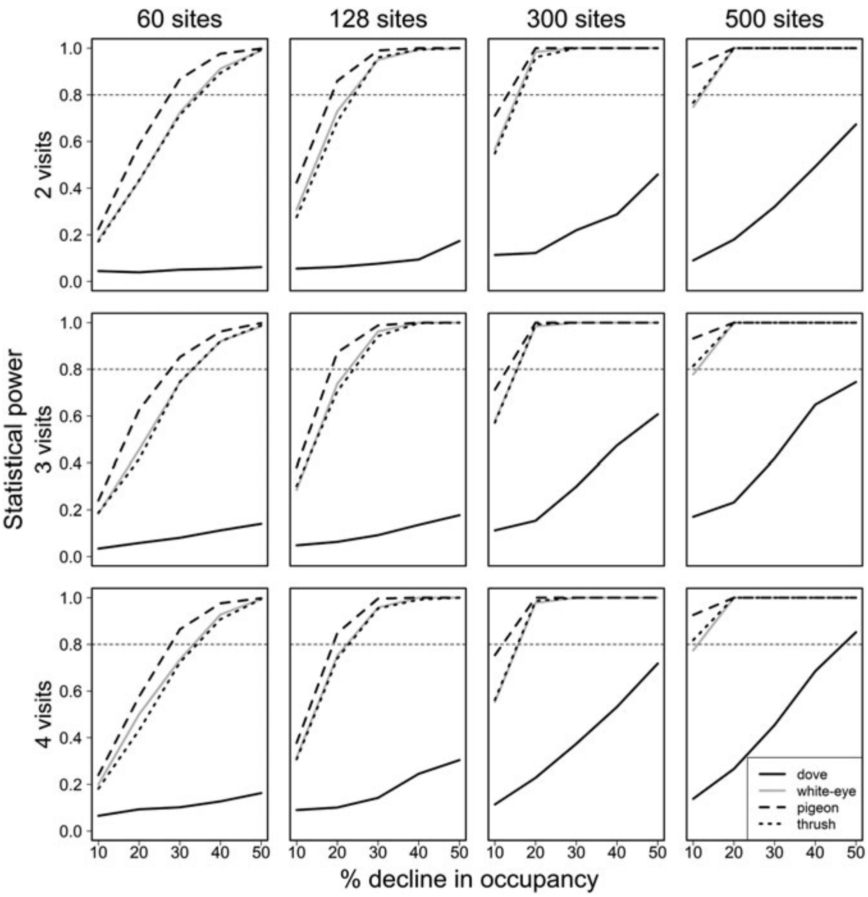

FIG. 4 Statistical power to detect declines in occupancy for four forest birds on Christmas Island: imperial pigeon, white-eye, thrush and emerald dove, under scenarios with a varying number of survey sites and repeat visits. All scenarios assume sites are surveyed every 2 years.

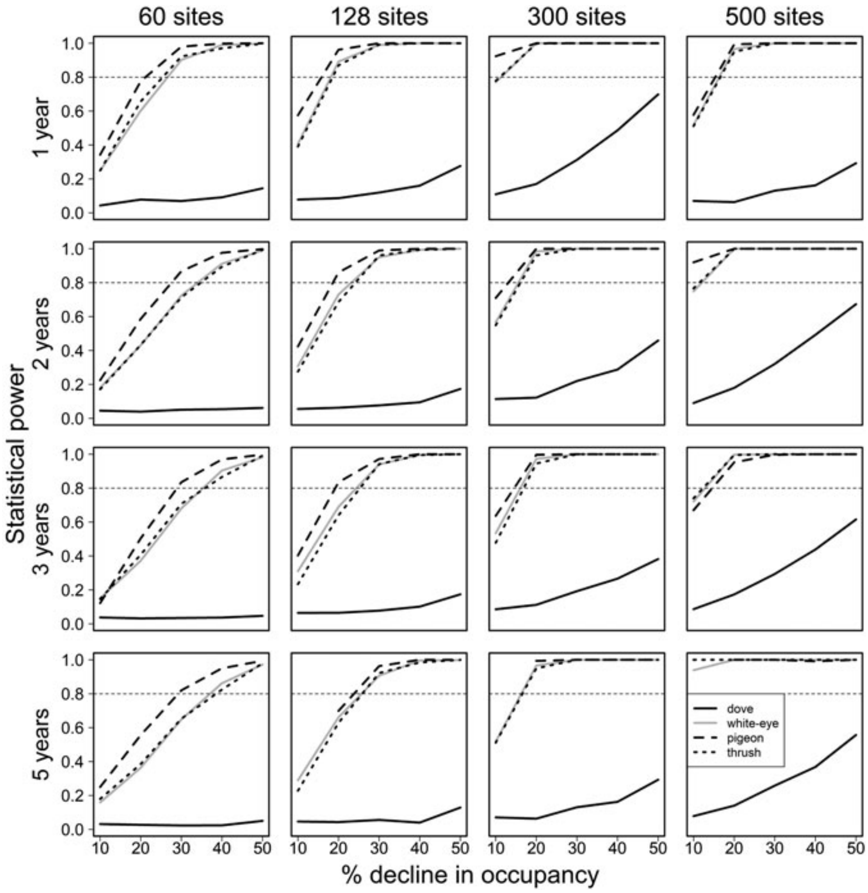

FIG. 5 Statistical power to detect declines in occupancy for four forest birds on Christmas Island: imperial pigeon, white-eye, thrush and emerald dove, under scenarios with a varying number of survey sites and interval between surveys. All scenarios assume sites are visited twice during each survey year.

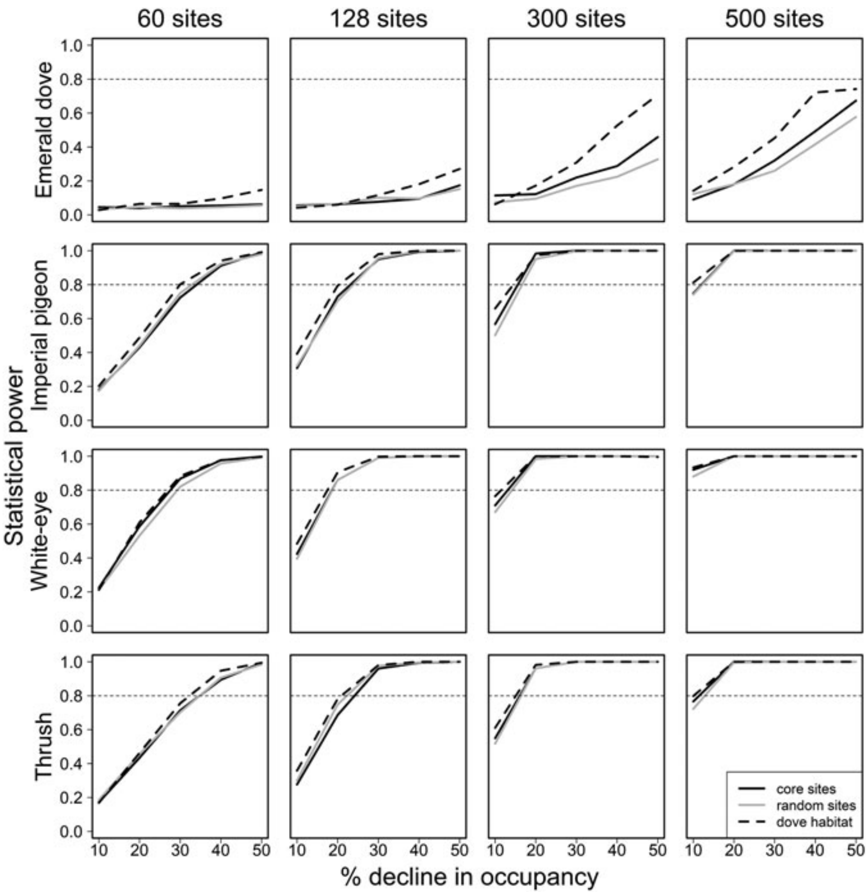

Fig. 6 Statistical power to detect declines in occupancy for four forest birds on Christmas Island: emerald dove, imperial pigeon, white-eye and thrush, under scenarios with a varying number of survey sites. The grey solid line represents power when sites are randomly selected across the island, the black solid line when the 128 core sites are monitored and the black dashed line when sites are targeted towards the most suitable dove habitat.

Discussion

In this study, we estimated single-visit detection probabilities from 3 years of repeat detection data for four forest bird species on Christmas Island, prioritized regions for surveys to complement the 128 core sites using occupancy maps, simulated declines in occupancy and monitoring data that may arise from alternative monitoring designs and calculated the statistical power of each monitoring design to detect the simulated trend. Many studies have used spatial prioritization tools to optimize survey locations (Amorim et al., 2014; Moran-Ordonez et al., 2018) or used statistical methods to inform survey effort (Steenweg et al., 2016; Southwell et al., 2019), but few studies have combined these components into a single monitoring design framework (Smart et al., 2022; Southwell et al., 2022).

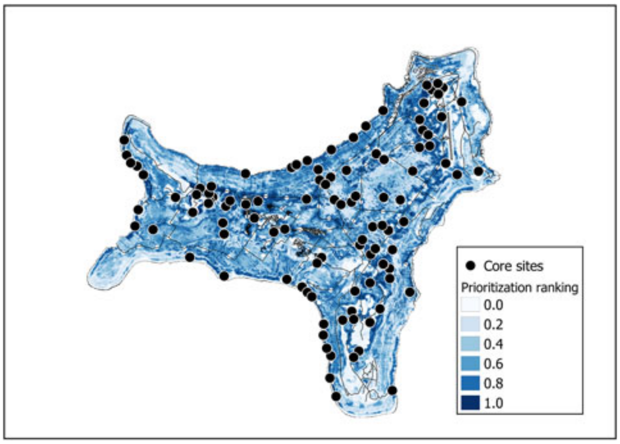

Fig. 7 The spatial prioritization of Christmas Island using *Zonation*, with yellow representing the highest-ranked cells for new surveys (1) and purple representing the lowest-ranked cells for new surveys (0). The black circles show the 128 core sites that were locked into the *Zonation* analysis.

Statistical power

Our results demonstrate that power to detect occupancy trends is highly sensitive to the number of sites surveyed and the magnitude of decline. Large declines over 10 years were more easily detected than small declines, and it was more difficult to detect declines in rare and cryptic species (emerald dove) than in widespread and common ones (imperial pigeon, white-eye and thrush). Increasing the number of repeat visits to sites within a survey year had relatively little influence on power because single-visit detection probabilities were high for the imperial pigeon, white-eye and thrush (0.839–0.904). Power to detect declines in these species was maximized by focusing effort on surveying more sites rather than on increasing the number of repeat surveys. However, the widespread distribution of these species meant that the exact placement of sites had little influence on power. Figure 6 shows that selecting sites at random, targeting the 128 core sites or prioritizing site placement using *Zonation* had little impact on the power curves.

In contrast, power to detect declines in the emerald dove was low for almost all scenarios tested. Even when 300–500 sites (including the core sites) were monitored, there was only sufficient power ($> 80\%$) to detect 40–50% declines in occupancy. Power was low for the emerald dove because both the single-visit detection probability (0.12) and the probability of occupancy were low (the mean probability of occupancy across the island was 0.19). More importantly, the species was highly restricted, preferring specific habitat types around the edge of the central plateau (Fig. 3). Only a fraction of the 128 core sites overlapped with areas where the species is predicted to occur, and for the sites that did, the chance of simulating detections if it was deemed present was low. This demonstrates that with rare and localized species, monitoring effort is wasted on sites where the species does not occur. It is far more efficient to survey only in areas where the species is either known to occur or is predicted to occur with high confidence. In some cases, monitoring occupancy may not be the most appropriate metric; abundance or relative abundance may be more sensitive to change.

Unsurprisingly, we found that power decreased as the interval between surveys increased because fewer data are used over a fixed time frame. We did, however, assume that the number of sites monitored on each occasion was constant, which may not always be the case. Power could increase with long intervals between surveys if the resources saved by not surveying every year are spent on surveying more sites (Einoder et al., 2018). An interesting extension of this research would be to develop a cost model that links the number of sites and survey frequency to a total budget (Smart et al., 2022). This would allow for the optimal survey frequency to be identified given an overall monitoring budget. The most appropriate survey frequency will also depend on the status and generation length of target species (i.e. it could be more important to monitor small populations that are close to extinction more frequently), the timescale at which target species are expected to respond to management and the risk tolerance of managers.

By conducting a spatial prioritization in *Zonation*, we compared power for alternative site placements across this island. Prioritizing site locations or targeting the 128 core sites did not increase power for the imperial pigeon, white-eye and thrush compared to selecting sites at random because these species are widespread. In contrast, power increased for the emerald dove when sites were prioritized spatially. For example, 128 randomly selected sites had a 0.15% chance of detecting 50% declines in the emerald dove. When the 128 core sites were surveyed, power slightly increased to 0.17, whereas purposely targeting sites with the most suitable habitat increased power to 0.27. This result is unsurprising; to detect change in a species' distribution, one must look where the species occurs. However, the optimal locations for monitoring sites are not always obvious in areas with many overlapping range-restricted species. To our knowledge, there are many examples where the placement of sites in monitoring networks is optimized using spatial prioritization tools (Amorim et al., 2014; Carvalho et al., 2016), but few examples where the number of sites needed to confidently detect change is also prioritized.

Assumptions and future research priorities

Like all simulations, our study was subject to limitations and assumptions. We used published maps of forest bird occupancy developed by Selwood et al. (2019) rather than fitting our own species distribution models. We attempted to fit dynamic occupancy detection models to the island-wide survey data to predict species occupancy for each year of monitoring. However, we decided against this approach because: (1) the maps by Selwood et al. (2019) were validated by experts and were used to inform future land use on the island, (2) our preliminary analysis suggested that the species distributions were relatively static over time, especially for the white-eye, thrush and imperial pigeon, (3) dynamic occupancy detection models have been shown to perform relatively poorly for widespread and common species if there is little turnover in site occupancy (Briscoe et al., 2021), and (4) boosted regression trees perform well at modelling interactions between predictor variables compared to dynamic occupancy detection models.

In addition, we weighted species equally in the spatial prioritization. Our approach could be expanded to place more value on rare or cryptic species such as the emerald dove. We simulated linear declines in occupancy over 10 years across a range of plausible effect sizes. Our approach could also be extended to include more complex temporal and/or spatial range dynamics, such as patterns in range contractions. Some species on Christmas Island, such as reptiles, have demonstrated clear range contractions coinciding with the spread of invasive species (Emery et al., 2021). Furthermore, we modelled trends in occupancy rather than trends in abundance over time and therefore assumed a constant relationship between occupancy and abundance (Stanley & Royle, 2005), meaning that all occupied cells declined in the same way regardless of how many individuals were within them.

Finally, we assumed that the goal was to detect trends with a targeted monitoring programme for four forest bird species rather than to develop a general surveillance programme for a larger suite of species. Thus, we estimated power based on the predicted distribution and detectability of these species only. We could repeat our analysis for more species if they were explicitly identified at the start as priorities. For example, there is a varied group of threatened terrestrial taxa on the island, including plants, seabirds and raptors, a flying fox and a single endemic reptile species (the giant gecko *Cyrtodactylus sadleiri*) persisting in the wild (Abbott, 2006). Adding more species to the analysis would probably result in a more even coverage of sites across the island but could reduce the power to detect change in range-restricted species with patchy distributions.

Conclusion

In this study, we present a framework that links species distribution modelling, detectability modelling and spatial prioritization to compare the performance of alternative monitoring designs. Without tools to support robust but efficient monitoring design, our understanding of declining species will continue to be obscured by limited data (Bates et al., 2014). We argue that spatial simulation tools that link correlative species distribution models with models simulating the observation process are needed to maximize chances of detecting species' responses to environmental change. 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 of meeting its objectives.

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Conflicts of interest None.

Ethical standards This research abided by the *Oryx* guidelines on ethical standards.

Data availability Data supporting this research are available to qualified researchers from the relevant government and non-government data providers under various data licensing agreements.

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