Received: 26 May 2021 | Revised: 27 April 2022 | Accepted: 6 July 2022

DOI: 10.1002/eap.2762

ECOLOGICAL APPLICATIONS
ECOLOGICAL SOCIETY OF AMERICA

ARTICLE

Designing a large-scale track-based monitoring program to detect changes in species distributions in arid Australia

Darren Southwell[1] | **Anja Skroblin**[1] | **Katherine Moseby**[2] | **Richard Southgate**[3] | **Naomi Indigo**[4] | **Brett Backhouse**[5] | **Keith Bellchambers**[6] | **Robert Brandle**[7,8] | **Peter Brenton**[9] | **Peter Copley**[7] | **Martin A. Dziminski**[10] | **Carolina Galindez-Silva**[11] | **Catherine Lynch**[8] | **Peggy Newman**[9] | **Reece Pedler**[2] | **Daniel Rogers**[7] | **David A. Roshier**[6] | **Ellen Ryan-Colton**[12] | **Katherine Tuft**[13] | **Matt Ward**[7] | **Damaris Zurell**[14,15] | **Sarah Legge**[4,12,16]

[1]School of Ecosystem and Forest Sciences, University of Melbourne, Parkville, Victoria, Australia

[2]University of NSW School of Biological, Earth and Environmental Science, Sydney, New South Wales, Australia

[3]Envisage Environmental Services, Kingscote, South Australia, Australia

[4]Centre for Biodiversity and Conservation Research, University of Queensland, St Lucia, Queensland, Australia

[5]Alinytjara Wilurara Landscape Board, Adelaide, South Australia, Australia

[6]Australian Wildlife Conservancy, Subiaco, Western Australia, Australia

[7]Department for Environment and Water, South Australian Government, Adelaide, South Australia, Australia

[8]South Australian Arid Lands Landscape Board, Port Augusta, South Australia, Australia

[9]Atlas of Living Australia, CSIRO National Collections and Marine Infrastructure, Docklands, Victoria, Australia

[10]Department of Biodiversity, Conservation and Attractions, Biodiversity and Conservation Science, Kensington, Western Australia, Australia

[11]Anangu Pitjantjatjara Yankunytjatjara Land Management, Alice Springs, Northwest Territories, Australia

[12]Research Institute for the Environment and Livelihoods, Charles Darwin University, Alice Springs, Northwest Territories, Australia

[13]Arid Recovery, Roxby Downs, South Australia, Australia

[14]Geography Department, Humboldt-University Berlin, Berlin, Germany

[15]Institute for Biochemistry and Biology, University of Potsdam, Potsdam, Germany

[16]Fenner School of Environment and Society, The Australian National University, Canberra, Australian Capital Territory, Australia

Correspondence
Darren Southwell
Email: darren.southwell@unimelb.edu.au

Funding information
Australian Government's National Environmental Science Program through the Threatened Species Recovery Hub; Australian Government Caring for Our Country; National Landcare Program grants; Government of South Australian; Australian Wildlife Conservancy; Jill

Abstract

Monitoring trends in animal populations in arid regions is challenging due to remoteness and low population densities. However, detecting species' tracks or signs is an effective survey technique for monitoring population trends across large spatial and temporal scales. In this study, we developed a simulation framework to evaluate the performance of alternative track-based monitoring designs at detecting change in species distributions in arid Australia. We collated presence–absence records from 550 2-ha track-based plots for

Landsberg Trust; Holsworth Wildlife Research Endowment

Handling Editor: Elisabeth Huber-Sannwald

11 vertebrates over 13 years and fitted ensemble species distribution models to predict occupancy in 2018. We simulated plausible changes in species' distributions over the next 15 years and, with estimates of detectability, simulated monitoring to evaluate the statistical power of three alternative monitoring scenarios: (1) where surveys were restricted to existing 2-ha plots, (2) where surveys were optimized to target all species equally, and (3) where surveys were optimized to target two species of conservation concern. Across all monitoring designs and scenarios, we found that power was higher when detecting increasing occupancy trends compared to decreasing trends owing to the relatively low levels of initial occupancy. Our results suggest that surveying 200 of the existing plots annually (with a small subset resurveyed twice within a year) will have at least an 80% chance of detecting 30% declines in occupancy for four of the five invasive species modeled and one of the six native species. This increased to 10 of the 11 species assuming larger (50%) declines. When plots were positioned to target all species equally, power improved slightly for most compared to the existing survey network. When plots were positioned to target two species of conservation concern (crest-tailed mulgara and dusky hopping mouse), power to detect 30% declines increased by 29% and 31% for these species, respectively, at the cost of reduced power for the remaining species. The effect of varying survey frequency depended on its trade-off with the number of sites sampled and requires further consideration. Nonetheless, our research suggests that track-based surveying is an effective and logistically feasible approach to monitoring broad-scale occupancy trends in desert species with both widespread and restricted distributions.

KEYWORDS
desert, detectability, ensemble models, indigenous tracking, sign-based tracking, simulation, statistical power, threatened species

INTRODUCTION

Biodiversity monitoring is crucial for determining trends in species and populations and how they respond to threat or management intervention (Possingham et al., 2012; Yoccoz et al., 2001). To be effective, monitoring must have clearly articulated objectives defined early in the design process (Lindenmayer et al., 2020), have sites positioned to overlap with the distribution or potential distribution of focal species (Steenweg et al., 2016), have sufficient resources to be sustained for the time needed to detect changes in ecological systems (Lindenmayer & Likens, 2018), account for biases such as imperfect detection (Mackenzie & Royle, 2005), and have adequate statistical power to detect a change of interest when one actually occurs (Southwell, Einoder, Lahoz-Monfort, Fisher, et al., 2019). Failing to account for these requirements can waste scarce conservation resources that would be otherwise better spent directly on management (McDonald-Madden et al., 2010).

An important consideration in the design of any monitoring program that seeks to detect a trend or change in a population is statistical power. Statistical power is the probability of correctly rejecting the null hypothesis of no change when a change in fact occurs (Taylor et al., 2007). It is influenced by many decisions during monitoring design, such as the choice of sampling method(s), the number and location of sites, and the intensity and frequency of sampling (Field et al., 2005). Limited budgets and logistical constraints impose trade-offs in these decisions that influence power; for example, increasing the number of sites might come at the cost of the time spent sampling sites. Many studies have used spatial prioritization tools to optimize survey locations (Amorim et al., 2014; Moran-Ordonez et al., 2018) or used simulation to determine the number of sites needed to detect population change (Southwell, Einoder, Lahoz-Monfort, Fisher, et al., 2019; Steenweg et al., 2016). However, to the best of our knowledge, no studies have combined these components into a single monitoring design framework.

Monitoring in arid regions around the world poses considerable challenges due to limited accessibility, the relatively sparse distribution and large movement patterns of species, and the difficulty in detecting individuals during surveys (Dickman et al., 2018). High variation in population dynamics in response to irregular rainfall-induced pulses in food resources also makes monitoring challenging (Letnic & Dickman, 2010; Moseby et al., 1999; Yang et al., 2010). In Australia, very little biodiversity monitoring has occurred in arid regions, despite the fact that these areas have experienced a substantial loss of species in recent decades: an estimated 60% of native mammal species in arid Australia are now extinct (Burbidge & McKenzie, 1989; Woinarski et al., 2014) and native species continue to be threatened by habitat degradation, changed fire regimes, introduced herbivores, and invasive predators. Large-scale monitoring coordinated across tenures is needed to understand further changes in the status, trends, and distributions of species in arid zones in response to climate change, threats, and management intervention.

Track-based monitoring offers a practical and rapid way to monitor cryptic species, or those found at low densities, over large spatial scales (Allen et al., 1996; Moseby et al., 2020; Southgate et al., 2005). It is relatively simple to implement and more cost-effective than trapping individuals or attempting direct counts (Caughley, 1977; Engeman, 2005). In arid Australia, a standardized 2-ha plot track-based monitoring protocol (also known as sign plots, tracking plots, sandplots; hereafter referred to as 2-ha plots) has been widely adopted by environmental consultants, Indigenous ranger groups, nongovernmental organizations (NGOs), and some government agencies for both surveillance and targeted monitoring of native (including threatened) and invasive species (Moseby et al., 2009; Southgate & Moseby, 2008). The approach is best suited to sandy substrates, favoring mammal, bird, and reptile species whose tracks are readily distinguishable, and builds on the strong tracking tradition of Indigenous Australians who continue to be the custodians of most desert regions.

Despite its widespread use over the last decade or more, 2-ha plot monitoring is usually conducted by individual organizations without any overarching coordination or attempt to collate and interrogate data across regional or national scales. Here, we suggest that a wider attempt to pool track-based data across arid Australia and coordinate monitoring efforts across jurisdictions and organizations could significantly contribute to an understanding of regional or national population trends in arid zone species if designed correctly. A coordinated national or regional 2-ha plot monitoring program would strengthen the quality and consistency of tracking protocols, showcase the conservation work being conducted by Indigenous and other groups in Australian deserts, promote more widespread and consistent use of the 2-ha plot technique, allow analysis of spatiotemporal trends, enable better understanding of ecological processes operating over large temporal and spatial scales, and enable the evaluation of broad-scale management actions (such as prescribed burning or predator control).

In this paper, we describe a general simulation framework for deciding where and how much survey effort is needed to detect changes in species occupancy. We applied our simulation framework to evaluate the performance of alternative 2-ha plot monitoring designs at detecting change in the distribution of vertebrates across a vast area ($\sim$700,000 km^2) of arid South Australia (SA). We collated 2-ha-plot data collected over the past 13 years in SA and fitted species distribution models (SDMs) to these data to predict the current distribution of 11 threatened and invasive vertebrates. Based on these maps, we simulated plausible changes in these distributions over the next 15 years, ranging from 10%–90% increases/decreases in occupancy. We then simulated monitoring data at 2-ha plots using realistic estimates of detectability and calculated the statistical power of three alternative monitoring scenarios: (1) surveys were restricted to existing 2-ha plots, (2) surveys were repositioned to optimally target all species equally, and (3) surveys were repositioned to optimally target two species of conservation concern.

We used our simulation approach to explore four questions: (1) Which predictors best explain the distribution of threatened and invasive species in arid SA? (2) How does the number of sites, within-year sampling, and monitoring frequency influence the power to detect occupancy trends? (3) Does power increase when new monitoring sites are established in regions with highest predicted occupancy? (4) Does the weighting of species change the optimal locations for surveys and power? Our approach will assess the likely performance of the existing 2-ha plot network at detecting population trends and prioritize regions to establish new plots depending on how species are weighted. Although we apply our simulation framework to evaluate a 2-ha plot network in arid Australia, it could easily be used to inform key design decisions for any large-scale biodiversity monitoring program where occupancy is the state variable of interest. Detecting population trends when they occur is crucial for avoiding species extinctions and for triggering timely management interventions.

METHOD

Study area

Our study area (728,481 km^2) included the sandy inland deserts of SA that fall within the Arid Lands and the Alinytjara Wilurara (AW) landscape regions (Figure 1a). The Arid Lands cover over half of SA, encompassing the state's northeast corner where pastoralism is the dominant land use. The AW landscape region in the state's northwest is composed mainly of Indigenous plus conservation lands. The study area covers nine bioregions, with habitats including low plains, stony plains, sandy desert dune fields, and ephemeral inland river systems. The region is extremely arid, with <200 mm annual rainfall in some parts. Rainfall rarely follows predictable cycles and is usually the result of episodic weather events (Morton et al., 2011).

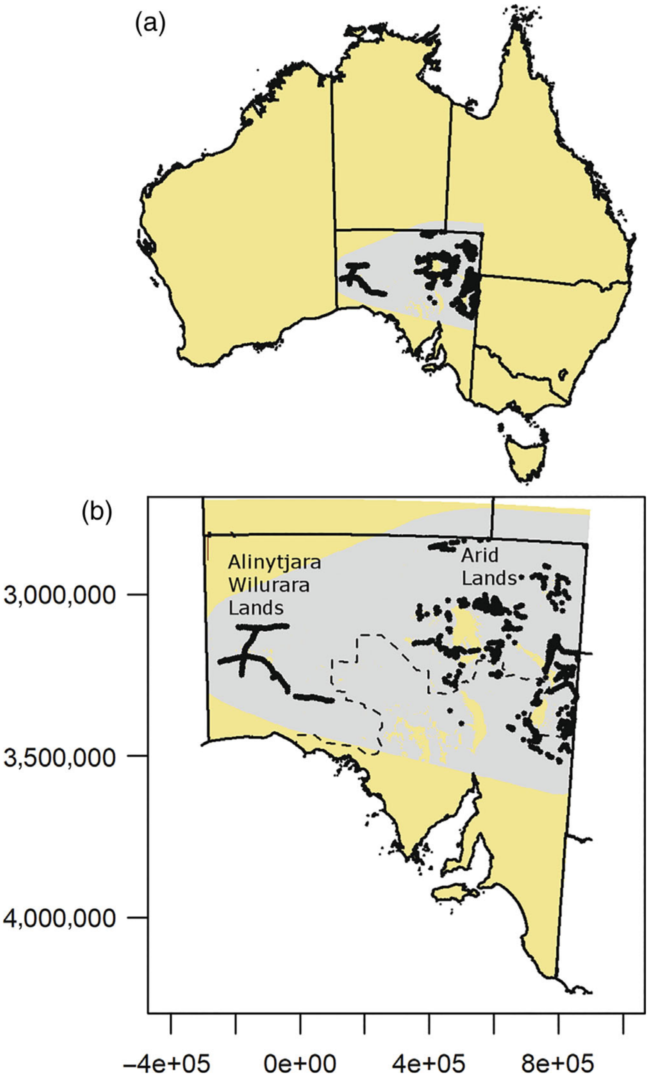

FIGURE 1 Location (black dots) of 2-ha plots in (a) Australia and (b) South Australia. The gray shaded region shows our study area. The black dotted line is the dog-proof fence, which was used as a predictor in species distribution models. Salt lakes or pans, which are inhospitable for our target species, were masked from the study area.

Target species

We held a 1-day workshop with relevant land management organizations to identify target species and objectives of any future 2-ha plot monitoring program in arid SA. In total, 15 species were of interest to decision makers, covering a range of taxa that we categorized into three broad groups:

1. Introduced species: camel (*Camelus dromedarius*), red fox (*Vulpes vulpes*), cat (*Felis catus*), rabbit (*Oryctolagus cuniculus*), and cow (*Bos taurus*, *Bos indicus*). Species in these groups have widespread distributions, and their sign is frequently recorded. Monitoring their distribution is important for understanding the level of threat they pose and informing management outcomes and priorities.
2. Native species with widespread distributions and of cultural significance to traditional owners: dingo (*Canis familiaris dingo*), bustard (*Ardeotis australis*), emu (*Dromaius novaehollandiae*), large macropods (*Osphranter rufus*, *Osphranter robustus, Macropus fuliginosus*), echidna (*Tachyglossus aculeata*), goanna (*Varanus* spp.), and malleefowl (*Leipoa ocellata*). Although species in this group have large distributions, they are not all common. For example, the malleefowl is of conservation concern because of ongoing population declines despite its large geographic range (Benshemesh et al., 2020).
3. Native species with limited distributions: crest-tailed mulgara (*Dasycercus cristacauda*), dusky hopping mouse (*Notomys fuscus*) and great desert skink (*Liopholis kintorei*). These species were considered priorities for regional conservation managers due to their conservation concern.

Collating and processing 2-ha-plot data

We negotiated data sharing agreements with data holders and collated 17 separate 2-ha-plot data sets collected between 2005 and 2018 (Figure 1b). In total, surveys were conducted by six to eight experienced field ecologists following a standardized protocol, with Indigenous ranger teams for some sites (Moseby et al., 2009). Observers searched each plot (100 × 200 m) for 25–30 min, with species recorded as present if there was evidence of tracks, diggings, burrows, or scats. Detected signs were aged as being 1–2 days old, 3–7 days old, or >7 days.

We pooled these data, producing a combined data set of 400 plots in the SA Arid Lands region and 150 plots in the AW region. Surveys in the AW NRM region were sometimes repeated within years. We collapsed these repeats and recorded a species as present if it was recorded at least once. We assumed a species was present regardless of the recorded age of sign/track.

Initial inspection of the data set revealed that the names of species or animal types had been idiosyncratically recorded (i.e., there was inconsistency between scientific and common names, diverging capitalization, and alternate punctuation or nomenclature). We created a naming key to group synonymous names using the tidyverse package in R (R Development Core Team, 2014) (Appendix S1).

Some species, such as hopping mice, could not be identified from their tracks to the species level in the field, but some species are known to have relatively distinct and separated geographic ranges. In consultation with experts, we assigned hopping mouse records as *Notomys fuscus* if they were recorded within this species' known geographic range. We discarded hopping mouse records from outside of this range because we could not confidently distinguish between two species that coexist in the southwest of the study area: *Notomys alexis* and *Notomys mitchelli*. Similarly, sympatric goanna species can be difficult to distinguish from tracks, as can sympatric large kangaroos; most records of these animals are made at the genus level, with only a small number of species records. We therefore grouped all goanna and kangaroo detections at the genus level.

Environmental predictors

We compiled a list of 20 environmental predictors used in previous studies that modeled the distribution of our target species (Table 1). Because our aim was to produce occupancy maps at a landscape scale, we were limited to predictors that were mapped across SA. We considered both static and dynamic variables. Static variables included climatic variables (eight Bioclim variables), terrain variables (elevation, topographic ruggedness, slope) and environmental variables (soil clay content, vegetation type, distance to permanent natural water features, distance to nearest agricultural land tenures, soil bulk density, soil calcrete content). We digitized a map of a 5400-km fence that runs through the middle of the study region to protect the sheep industry from dingoes (Figure 1). This fence is thought to limit the distribution of larger-bodied species, such as dingoes, emus, and cattle. We included two dynamic variables in our SDMs: total annual rainfall and mean Normalized Difference Vegetation Index (NDVI) for each survey year. We calculated total annual rainfall in the year prior to the first survey so that the effect of a 1-year lag could be explored (see Table 1 for descriptions of each variable). We obtained raster layers of each variable and extracted values at 2-ha plots using the raster package (Hijmans & van Etten, 2012) in R after resampling each to a resolution of 1 km. We standardized all covariates by their mean and standard deviation prior to model fitting.

Fitting SDMs

We developed dynamic SDMs to predict species occupancy across the study area. We fitted models using the complete data set and predicted occupancy in 2018. Prior to model fitting, we reduced our candidate set of predictors following two steps. First, we assessed the univariate importance of each predictor on species occupancy by fitting generalized additive models (GAMs). We calculated pairwise Spearman correlation coefficients and removed predictors with the lowest univariate importance from highly correlated pairs ($|r| > 0.7$) (Dormann et al., 2013). Second, to avoid overfitting, we removed predictors with the lowest univariate importance until the ratio between the number of predictors (including quadratic terms) and the number of presences/absences (whichever was lowest) was greater than 20 (Harrell, 2001). This resulted in a unique set of predictors for each species. At this point, the great desert skink, echidna, and malleefowl were excluded from our analysis due to insufficient detections.

We adopted an ensemble approach to building SDMs (Araujo & New, 2007) by fitting models using three algorithms: generalized linear models (GLMs), boosted regression trees (BRTs), and random forests (RFs). Ensemble modeling is considered best practice in many fields of forecasting (such as climate science) because multimodel averages often yield better predictions than a single model (Johnson & Omland, 2004). For each algorithm we assumed a binomial error distribution with logit link. GLMs were fitted to predictors with both linear and quadratic terms using backward stepwise selection to find the combination of terms with the lowest ranked AIC value (Akaike, 1973). BRTs were estimated using the dismo package (Hijmans et al., 2011), with a tree complexity of 2, a bag fraction of 0.75, and a learning rate of 0.01 (Elith et al., 2008). RFs were fitted with 1000 trees and a minimum node size of 20 in the randomForest package (Liaw & Wiener, 2002).

TABLE 1 Summary of predictor variables used to build species distribution models. Predictor variables are grouped as climatic, topographic, or environmental; they were selected on the basis of reviews of previous work (cited in Column 6, "Justification") that examined the distribution(s) of species considered in this study.

Predictor	Source	Resolution	Range/unit	Static/dynamic	Justification
Climatic					
Annual mean temperature	BioClim (Bio1)[a]	1 km	14.4 to 23.4 (°C)	Static	Relevant to vegetation growth (Roy-Dufresne et al., 2019; Legge et al., 2017)
Annual rainfall	Australian Water Availability Project (AWAP) (Jones et al., 2009)	5 km	0.70 to 335.6 (mm)	Dynamic	Relevant to vegetation growth and soil water content (Southgate & Moseby, 2008; Allen et al., 2018; Letnic & Dickman, 2006; Roy-Dufresne et al., 2019)
Temperature annual range	BioClim (Bio7)[a]	1 km	23.4 to 34.5 (°C)	Static	Relevant to vegetation growth
Temperature seasonality	BioClim (Bio4)[a]	1 km	3.9 to 6.7 (°C)	Static	Relevant to vegetation growth (Roy-Dufresne et al., 2019)
Isothermality (mean diurnal range/ annual temperature range)	BioClim (Bio3)[a]	1 km	0.42 to 0.52	Static	Relevant to vegetation growth
Mean diurnal temperature range	BioClim (Bio2)[a]	1 km	11.4 to 15.9 (°C)	Static	Relevant to vegetation growth
Maximum temperature in warmest month	BioClim (Bio5)[a]	1 km	28.9 to 39.9 (°C)	Static	Some species (i.e., rabbit) cannot tolerate extremely high temperatures (Roy-Dufresne et al., 2019; McDonald et al., 2015)
Minimum temperature in coldest month	BioClim (Bio6)[a]	1 km	1.3 to 6.6 (°C)	Static	Some species (i.e., rabbit) cannot tolerate extremely low temperatures (Roy-Dufresne et al., 2019; Southgate et al., 2007)
Precipitation in wettest month	BioClim (Bio13)[a]	1 km	40.7 to 146.0 (mm)	Static	Relevant to vegetation growth and soil water content
Topographic					
Elevation	GeoScience Australia	100 m	−20.7 to 981.5 (m)	Static	Can influence vegetation type and temperature (Southgate et al., 2007; Skroblin et al., 2019)
Terrain roughness	GeoScience Australia	100 m	0 to 558.6	Static	McDonald et al. (2015); Legge et al. (2017); Skroblin et al. (2019)
Slope	GeoScience Australia	100 m	0 to 21.8 (°C)	Static	Can influence runoff and moisture availability

(Continues)

TABLE 1 (Continued)

Predictor	Source	Resolution	Range/unit	Static/ dynamic	Justification
Environmental					
Percentage soil clay content	CSIRO, Australia[b]	1 km	4.3 to 54.9 (%)	Static	Can be a proxy for drainage, fertility, and vegetation type (Allen et al., 2018; Roy-Dufresne et al., 2019; Stafford Smith & Morton, 1990; Roy-Dufresne et al., 2019)
Soil bulk density	CSIRO, Australia[b]	1 km	0.82 to 1.61	Static	Can be a proxy for drainage, fertility, and vegetation type
Soil calcrete	CSIRO, Australia[b]	1 km	−0.3 to 1	Static	Can be a proxy for drainage, fertility, and vegetation type (Southgate et al., 2007)
Distance to nearest permanent water features	GeoScience Australia	1 km	0 to 1.96	Static	Permanent water can be a good proxy source to find perennial vegetation and vegetation with greater percentage of water content (Roy-Dufresne et al., 2019; Allen & Fleming, 2012)
Annual NDVI	Google Earth Engine (Gorelick et al., 2017)	1 km	−945 to 5511	Dynamic	Can be a more direct measure of vegetation condition and soil moisture than rainfall (McDonald et al., 2015; Young et al., 2022)
Distance to agricultural areas	South Australia Government Data Directory[c]	1 km	0 to 408 (km)	Static	Pasture is an important source of food for some species such as rabbits (McDonald et al., 2015; Roy-Dufresne et al., 2019)
Dog-proof fence	Government of South Australia Department of Primary Industries and Regions	1 km	1 (inside fence), 0 (outside fence)	Static	The fence may limit movement of larger-bodied species

[a] http://www.worldclim.org/bioclim.

[b] http://www.asris.csiro.au/.

[c] https://data.sa.gov.au/data/dataset/land-use-aclump.

Model evaluation

We conducted cross-validation to measure the predictive performance of our models. We calculated four different performance measures for each SDM: sensitivity (proportion of observed presences that are correctly predicted); specificity (proportion of observed absences that are correctly predicted); true skill statistic (TSS), which indicates how well the model separates presences from absences; and area under the receiver operating characteristic curve (AUC). An AUC value of 0.5 indicates a model performing no better than a randomly generated one, whereas an AUC of 1 indicates optimal performance (Pearce & Ferrier, 2000). Cross-validation was conducted with the packages PresenceAbsence (Freeman & Moisen, 2008) and ecospat (Di Cola et al., 2017).

Predicting probability of occurrence

We predicted the probability of occupancy of each species in SA using an ensemble approach. We resampled all raster layers at a resolution of 1 km and predicted the probability of occupancy in 2018 with each of the three algorithms using the yearly raster layers of mean NDVI and total rainfall for that year. We calculated the ensemble projection by averaging across the three algorithms, weighted by their cross-validation TSS score (Araujo & New, 2007). To avoid predicting outside of the environmental domain sampled, we masked predictions to within a 50-km buffer around the sampled 2-ha plots. We checked that the environmental domain of the 2-ha plots was representative of this prediction space (Appendix S2). We also masked out dry lakes, pans, and water bodies where species were unlikely to occur.

Simulating changes in occupancy and estimating statistical power

We used a spatially explicit simulation tool developed by Southwell, Einoder, Lahoz-Monfort, Gillespie, et al. (2019) to estimate the statistical power of alternative 2-ha-plot monitoring designs at detecting future occupancy trends. 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, 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 plot, 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 modeled trend in occupancy is detected from the simulated data sets (Figure 2). A more detailed description of the simulation framework can be found in Southwell, Einoder, Lahoz-Monfort, Gillespie, et al. (2019).

We used the ensemble SDMs developed as described earlier to initiate simulations and provide a realistic snapshot of the current distribution of priority species. We obtained single-visit detection probabilities for 2-ha-plot surveys for seven species (hopping mouse, dingo, fox, cat, camel, rabbit, kangaroo) from Southgate et al. (unpublished) (Appendix S3). For species without detection estimates, we assumed that detectability was equal to the most similar species listed previously in terms of body mass and size of the sign/track (Garrard et al., 2013). For example, we assumed that the detectability of the crest-tailed mulgara and dusky hopping mouse sign was equal to the hopping mouse. A full list of detectability estimates is provided in Appendix S3.

Monitoring scenarios

We estimated power for three alternative 2-ha-plot monitoring design scenarios that focused on different target species groups. In Scenarios 1 and 2, the monitoring objective was to detect simulated changes in occupancy across all three species target groups (introduced species, native species with widespread distributions, and native species with limited occupancy). In Scenario 3, the monitoring objective was to detect simulated changes in occupancy for species of conservation concern (dusky hopping mouse, crest-tailed mulgara).

In Scenario 1, we surveyed existing 2-ha plots only. In Scenarios 2 and 3, we identified new locations for 2-ha plots using the spatial prioritization tool Zonation (Lehtomaki & Moilanen, 2013). Zonation uses a reverse stepwise heuristic to iteratively remove cells from the landscape based on the biodiversity value (in this case occupancy), connectivity, and representation of biodiversity features (in our case, species). Cells are ranked from 0 (lowest priority) to 1 (highest priority) (Cabeza et al., 2004).

We ran Zonation using the ensemble SDMs as biodiversity features (1-km resolution). We ran all analyses using the "core area" function with a warp factor of 1000 (the number of cells removed each iteration). In Scenario 2, we ran the prioritization for all species to ensure adequate representation. In Scenario 3, we ran Zonation for the two native species with limited distributions only (dusky hopping mouse, crest-tailed mulgara), so that the positioning of plots in the landscape targeted just these species. In both scenarios, we randomly selected plot locations from the top ranked 10% of cells in the landscape.

For all three scenarios, we varied the number of plots surveyed from 50 to 700, the number of within-year repeats from one to three, and the survey frequency from

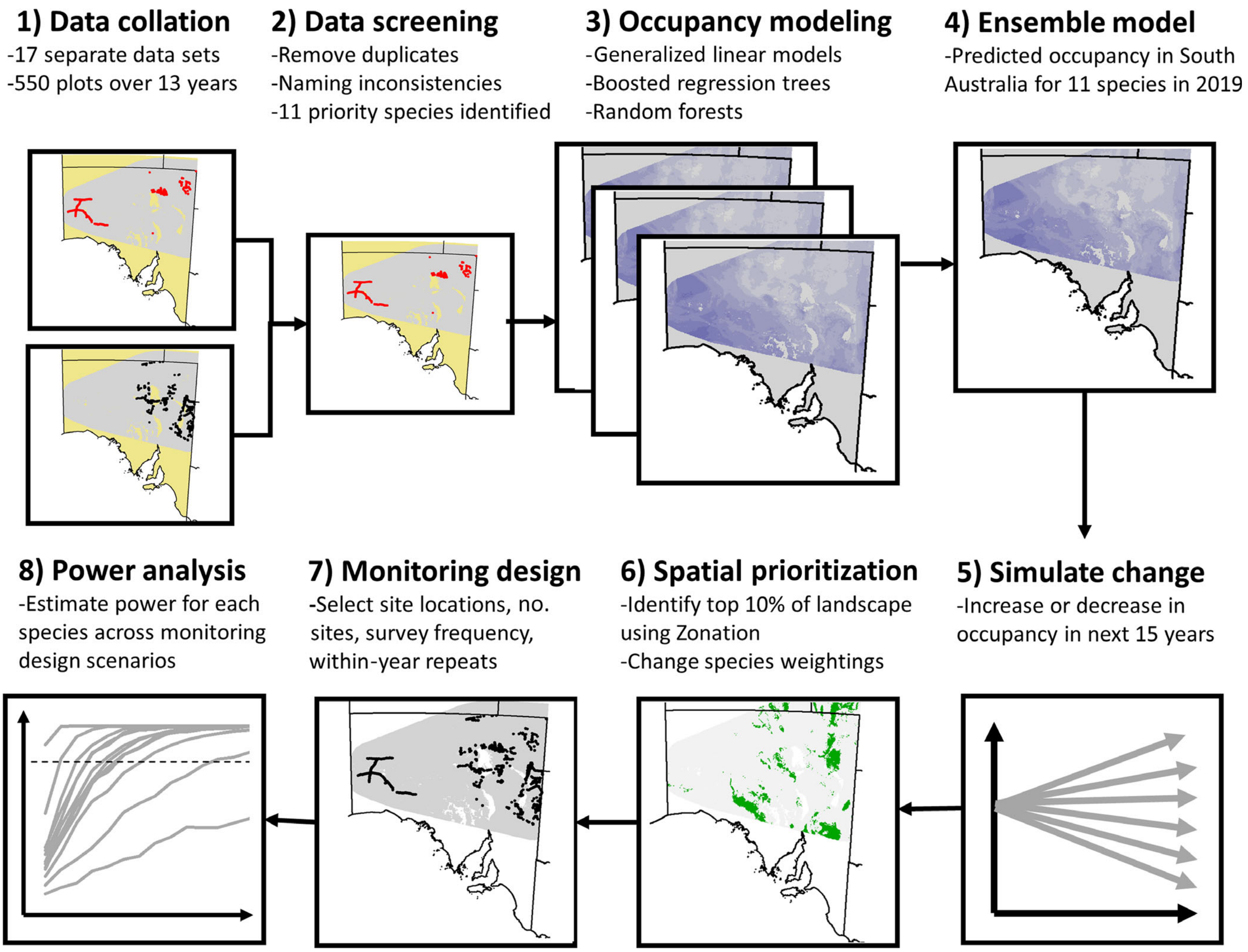

FIGURE 2 Conceptual diagram of spatially explicit power analysis framework.

1 to 5 years. We also explored a monitoring design where there was a simple trade-off between survey frequency and the number of plots, such that the total number of plots surveyed over the monitoring horizon remained constant (see Appendix S6 for details). For each scenario and design, we tested power to detect both increasing and decreasing trends in species occupancy, ranging from 10% to 90% of current levels. In all cases, we ran 1000 simulations (n) for each scenario, species, and effect size and conducted a two-tailed test with a type I error rate of $\alpha = 0.05$ to calculate power. A summary of the simulation framework is presented in Figure 2.

RESULTS

All species listed at the stakeholder workshop were detected at least once during surveys. After collapsing within-year surveys, the most commonly detected species was the dingo ($n = 878$), followed by the rabbit ($n = 804$), fox ($n = 780$), camel ($n = 635$), cow ($n = 582$), cat ($n = 534$), dusky hopping mouse ($n = 304$), crest-tailed mulgara ($n = 266$), emu ($n = 257$), goanna ($n = 203$), kangaroo ($n = 186$), bustard ($n = 79$), echidna ($n = 35$), great desert skink ($n = 19$), and malleefowl ($n = 18$). We fitted SDMs to 11 of these species; the bustard, echidna, great desert skink, and malleefowl were excluded due to relatively few detections.

Predictor variables

Climate variables showed the highest cross-validated univariate importance for most species compared to topographic or environmental variables. For the climatic predictors, isothermality was ranked in the top three predictors for nine of the 11 species, followed by temperature seasonality (seven species), mean diurnal temperature range (four species), annual mean temperature (two species), and a 1-year lag in yearly rainfall (two species).

The most important topographic predictors were soil clay content and soil calcrete content; however, these were ranked in the top three variables for only two species each. The dog-proof fence had little influence on the distribution of species except for the emu. The ensemble univariate response of predictors for each species is presented in Appendix S4.

Species distribution models

Mean predictive performance of the ensemble SDMs was high (AUC, range 0.87–0.95) for all species (Appendix S5). RF was consistently the best performing algorithm in terms of AUC, TSS, sensitivity, and specificity compared to BRTs and GLMs. Our ensemble SDMs predicted rabbits and dingoes to be most widespread across arid SA. Foxes and cats were also relatively widespread but had lower predicted occupancy in the northeast part of the study region. In contrast, dusky hopping mice and crest-tailed mulgara were predicted to occur in the central and northeast of the study region (Figure 3).

Number of 2-ha plots, within-year repeats and frequency

Across all scenarios, power increased as the number of plots and within-year surveys increased (Figure 4). Our simulations suggest that surveying 100 plots twice per year has a greater than 80% chance at detecting 30% declines in occupancy for one of the 11 species modeled (fox) over the next 15 years (Figure 5). This increased to eight of the 11 species when we assumed a 50% decline in occupancy (kangaroo, emu, and goanna had <80% power). Increasing the number of plots to 200 improved power to detect declines in all species. There was less than an 80% chance at detecting 30% declines in five of the 11 species (fox, dingo, cow, rabbit, and camel) and a 50% decline in ten of the 11 species. Surveying 500 plots twice per year detected 30% declines in all species except for the kangaroo.

For any given effect size and number of plots, there was a higher chance of detecting increasing occupancy trends compared to decreasing trends. Power decreased for all species as the years between surveys increased when the number of plots surveyed remained constant (Figure 5). In contrast, power was generally stable or increased as the years between surveys increased when there was a simple trade-off in the number of sites and survey frequency. This was because the number of plots surveyed on each occasion increased by a large amount as the years between surveys increased.

Optimal location of 2-ha plots

Targeted monitoring toward regions ranked in the top 10% by Zonation resulted in gains in power for most species (Figure 6). When all target species groups were included in the prioritization (Scenario 2), power to detect 30% declines in occupancy increased for the most widespread native species and two species with restricted distributions—crest-tailed mulgara (14%), kangaroo (20%), dusky hopping mouse (16%), emu (21%), and goanna (15%)—compared to when the existing network of plots were monitored (Figure 5). When plots were positioned based on the predicted distribution of the two range-restricted species (dusky hopping mouse and crest-tailed mulgara; Scenario 3), the power to detect 30% declines in these species increased by 31% and 29%, respectively, compared to when the existing network of plots was surveyed (Figure 5). In this scenario, only around 150 plots are needed to detect 30% declines in the occupancy of these two species with approximately 90% power.

DISCUSSION

While 2-ha-plot surveys have been conducted across arid Australia for almost two decades, there has been no attempt to assess the survey effort needed at regional or national scales to detect occupancy trends over time. In this study, we collated 2-ha-plot data from 17 data sets in arid SA, screened data for inconsistencies in species records, developed SDMs, identified new regions for surveys using spatial prioritization software assuming three monitoring scenarios (focusing on all or one of three species target groups), and applied a spatially explicit simulation tool to evaluate the likely performance of alternative monitoring designs at detecting occupancy trends. 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 determine the number of sites needed to detect population change (Southwell, Einoder, Lahoz-Monfort, Fisher, et al., 2019; Steenweg et al., 2016). However, to our knowledge, this is the first study that combines these components into a single monitoring design framework.

Influence of design decisions on power

For any given monitoring design and effect size, there was a higher chance at detecting increasing occupancy trends compared to decreasing trends. This is because

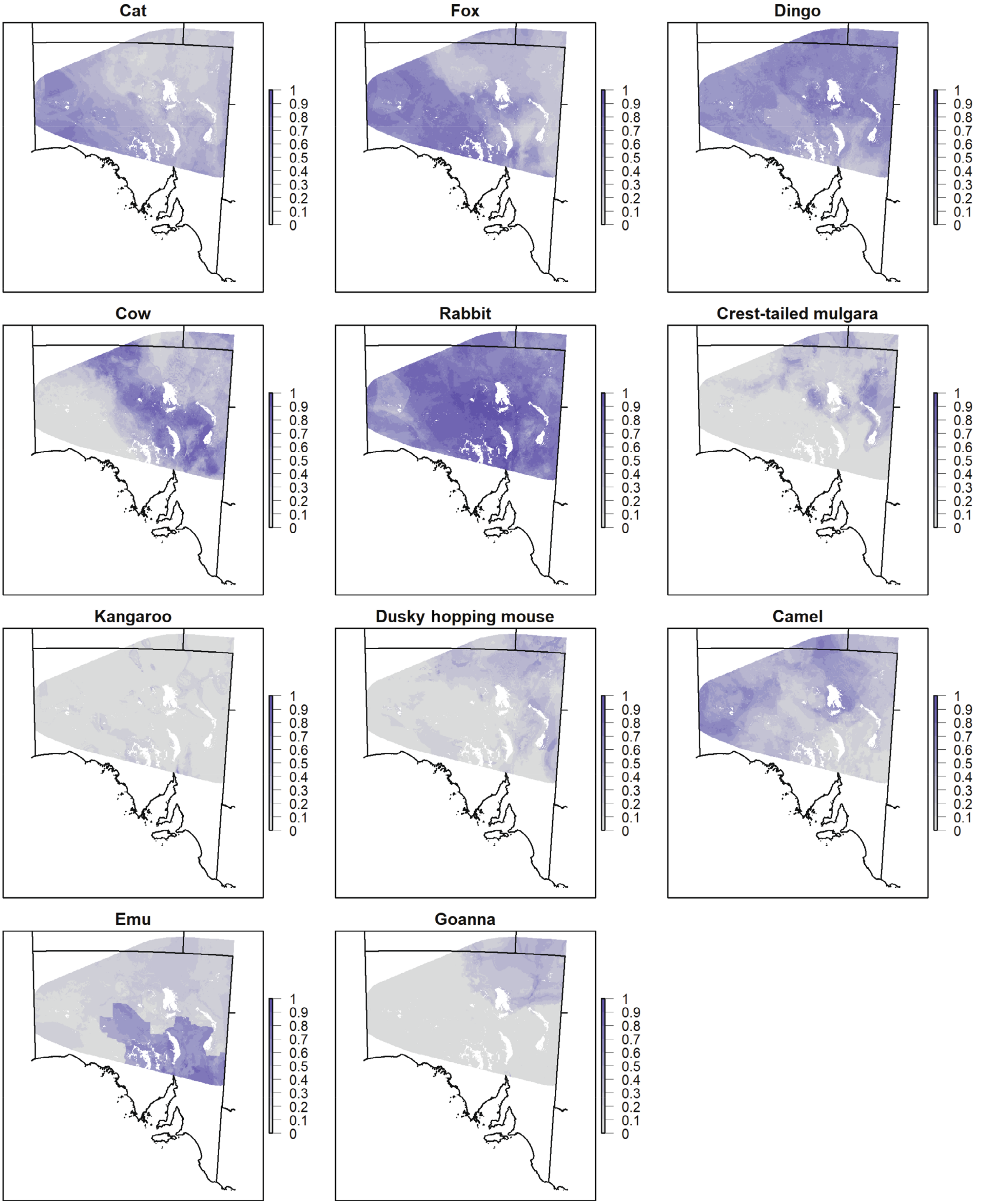

FIGURE 3 Predicted probability of occupancy for target species from ensemble species distribution models ranging from 0 (light gray) to 1 (dark blue). Predictions are constrained to the study area, with salt lakes or pans, which are inhospitable for these species, masked as white.

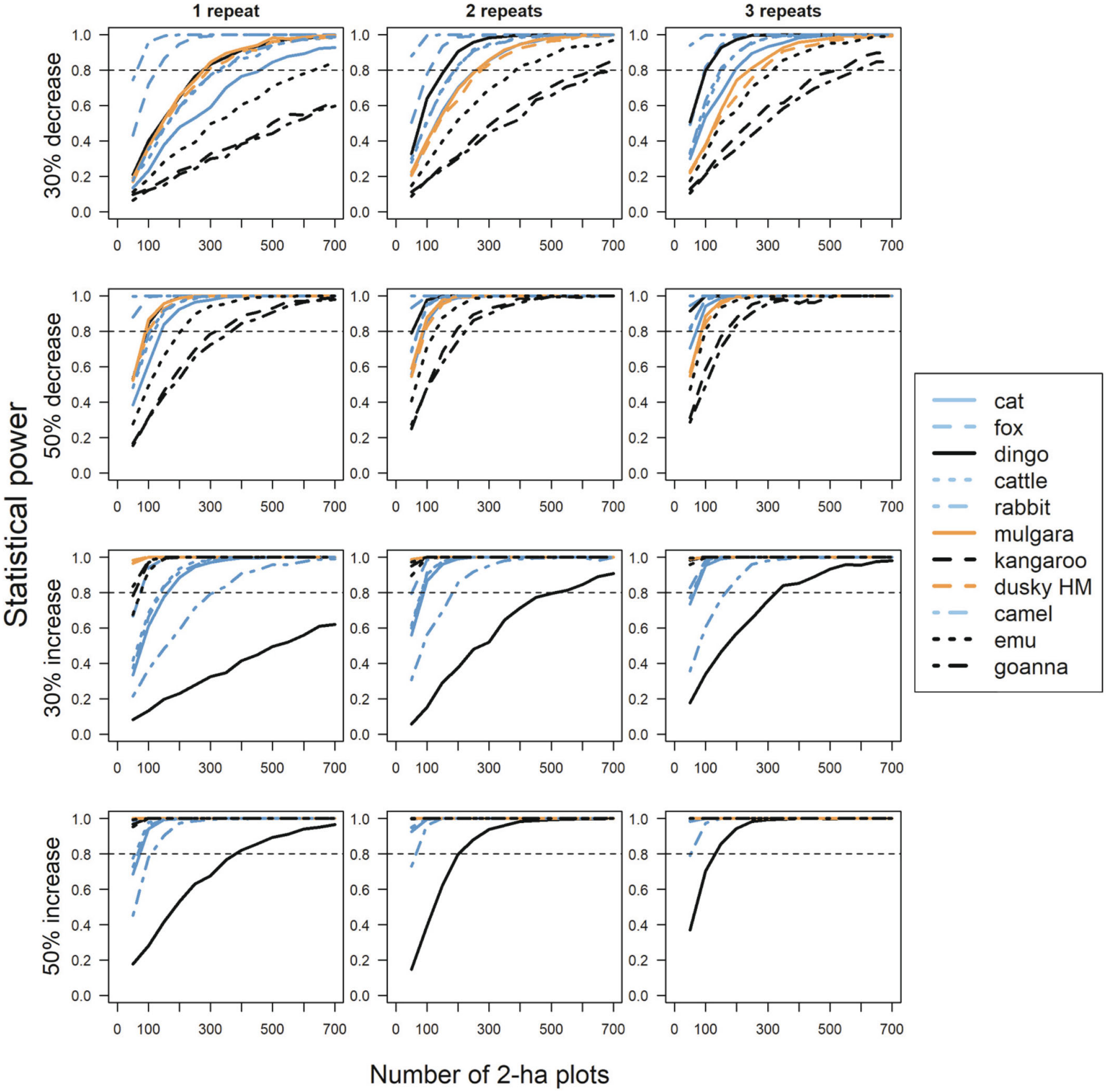

FIGURE 4 Statistical power (*y*-axis) to detect occupancy trends in 11 species over 15 years depending on number of 2-ha plots surveyed each year (*x*-axis), the magnitude of change (30% or 50%), the direction of change (increasing or decreasing), and the number of within-year repeat surveys (1–3). The dashed horizontal line represents 80% power.

species occupancy at the start of simulations was closer to zero than one, which meant that an increasing trend resulted in a larger absolute change in occupancy for a given effect size. The implication of this result is that designing a monitoring program to detect increases in species occupancy may not have sufficient power to also detect declines. Having adequate power to detect declines is especially important to ensure that populations do not unknowingly reach critically low levels. Our simulations suggest that monitoring 200 plots of the existing network has an 80% chance at detecting 30% declines in five of the 11 species. These species included four introduced species and the dingo, which are widespread and relatively common. Surveying 200 plots annually should be feasible given that 187 plots were surveyed on average each year in our data set. However, if the goal is to detect 30% declines in the rarer species with limited distributions, then more of the existing 2-ha-plot network should be surveyed or new plots should be established in areas with the higher predicted occupancy for these species. For

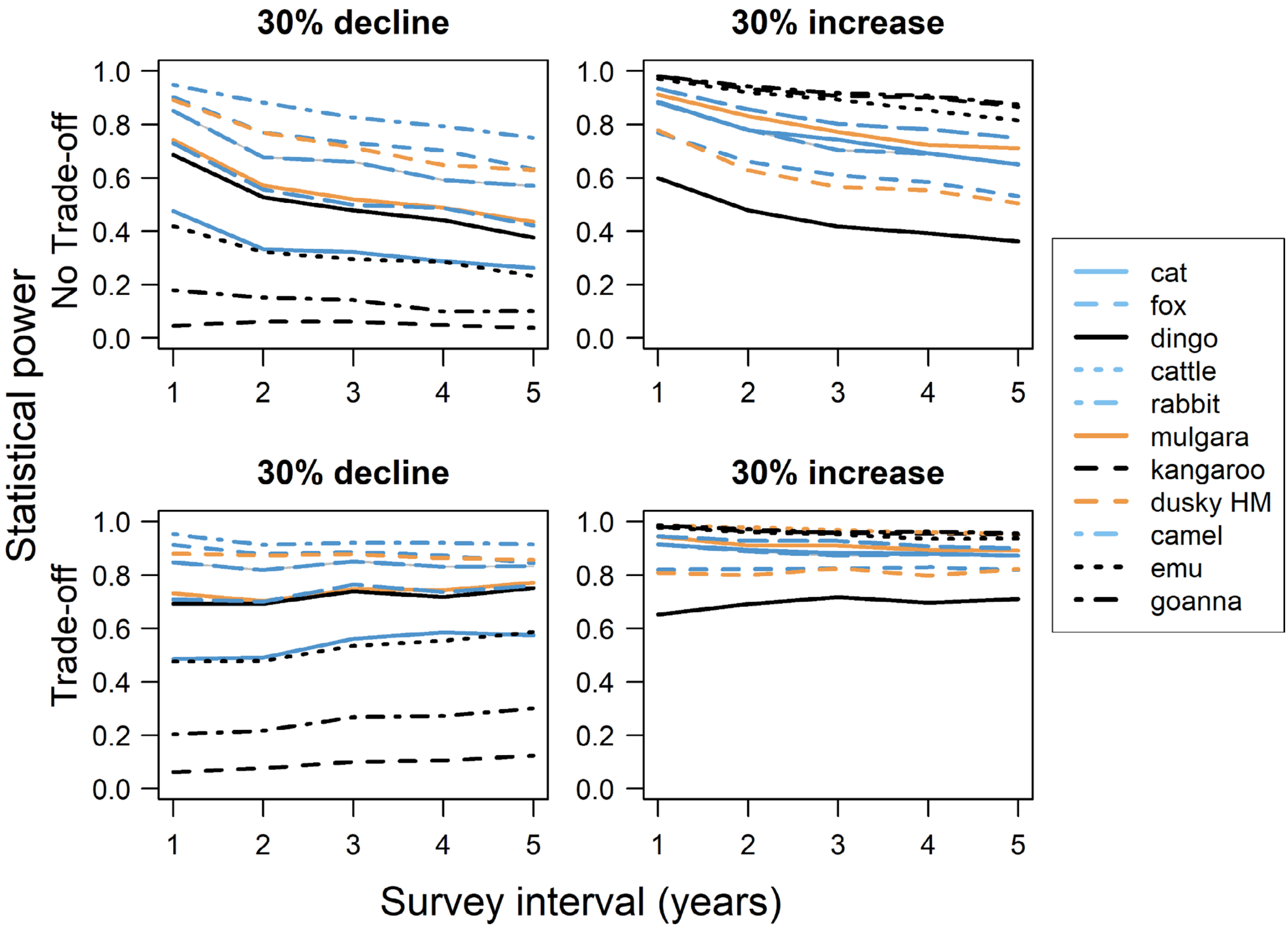

FIGURE 5 Power (*y*-axis) to detect 30% declines (left) and 30% increases (right) in occupancy when the time between surveys increases from 1 to 5 years. In the top row, the same number of plots are surveyed in each survey year regardless of the time between surveys. In the bottom row, the number of plots surveyed in each survey year increases as the time between surveys increases so that the total number of surveys over 15 years remains constant.

example, the power to detect 30% declines in the crest-tailed mulgara and dusky hopping mouse when 200 of the existing sites were monitored was 0.69 and 0.62, respectively. However, this increased to 0.94 and 0.88 in Scenario 3 when 150 plots were repositioned in the top 10% of habitat for these species.

Although power was highly sensitive to the number of plots, it was influenced to a lesser extent by the number of repeat surveys within a year. Across all species and scenarios, increasing the number of within-year surveys increased the power to detect occupancy trends. The gain in power was generally greater when the number of within-year surveys increased from one to two compared to two to three. Importantly, sign can go undetected by observers during 2-ha-plot surveys even by experienced field ecologists. Plots, or a subset of plots, should therefore be surveyed twice a year across different parts of the landscape so that detectability can be explicitly accounted for when estimating occupancy trends (MacKenzie et al., 2002). However, given the remoteness of most 2-ha plots, it will not be practically feasible to resurvey all plots twice each year. There is little guidance in the occupancy-detection literature on how monitoring effort should be spent between the number of sites surveyed and the number of repeat surveys. Mackenzie and Royle (2005) recommended surveying more sites less intensively for rare species and fewer sites more intensively for common species. To explore this further, we ran an additional scenario that changed the proportion of plots resurveyed with the total number of plots fixed at 200 (Appendix S7). We found that resurveying only a small subset of the 200 (i.e., <20) was still sufficient to account for detectability when estimating occupancy trends, resulting in very little loss of power.

An important consideration in any monitoring program is the survey frequency. More effort can sometimes

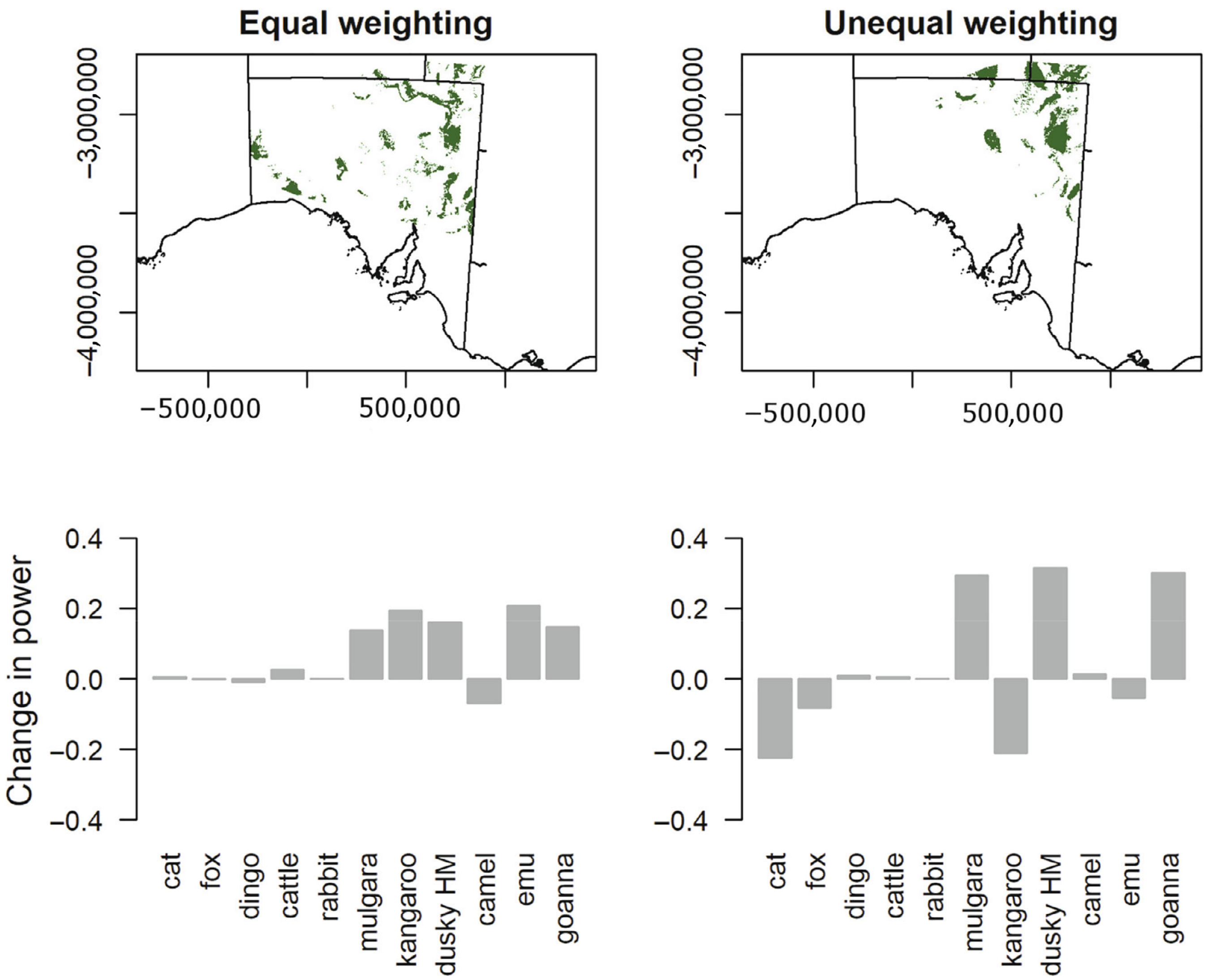

FIGURE 6 Top 10% of cells prioritized by Zonation (green; top row) when all species are weighted equally (left) and when the species with limited distributions, crest-tailed mulgara and dusky hopping mouse, are prioritized (right column). The bottom row shows the change in power to detect 30% declines in occupancy when 200 plots are targeted toward the highest ranked cells compared to existing plots.

be allocated to the number of plots, or the time spent at plots, if monitoring is not required regularly (Einoder et al., 2018). We explored monitoring scenarios where the survey frequency varied from 1 to 5 years with and without a simple trade-off in the number of plots surveyed on each occasion (Appendix S6). Not surprisingly, surveying less frequently reduced power, assuming the same number of plots is surveyed on each occasion. In contrast, power stabilized or increased slightly as survey frequency increased when a simple trade-off with the number of plots was imposed. However, this result should be treated with caution because the optimal survey frequency will depend critically on the relationship between frequency and the number of sites, and it is unlikely to be linear in practice. The most appropriate survey frequency should also depend on additional factors not considered in our framework, such as logistical constraints, the status of target species (i.e., it might be more important to monitor threatened species with small populations more frequently), and the generation length of target species. Monitoring frequency should also be synchronized, if possible, with natural peaks and troughs in populations, which is particularly challenging in arid Australia because "boom-bust" cycles are irregular and difficult to anticipate (Dickman et al., 2018).

Using the spatial prioritization software Zonation, we evaluated power with plots targeted toward regions of highest predicted occupancy across all species (Scenario 2) as well as only toward two species of conservation concern (Scenario 3). Optimizing the locations of plots across all species generally increased power for most when compared to the existing network (Scenario 2), with the exceptions of the cat and the camel, because these species are widespread and common. However, gains in power were relatively small, probably because the existing network is relatively extensive and already targets high-quality habitat (Pedler et al., 2016). Repositioning plots to target the dusky hopping mouse and crest-tailed mulgara (Scenario 3) further increased power for these species, but this came at the cost of decreasing power for others, such as the cat and emu, which were predicted to be less prevalent in this part of the study region. Optimizing site locations also did not increase power to sufficient levels to detect 10% declines in these species. This component of our analysis demonstrates how the monitoring objective and target species must be defined early in the design stage because they have substantial influence on survey location and effort.

We could not fit SDMs for four species (bustard, malleefowl, echidna, great desert skink) because either there were too few detections or detections were too clumped in geographic space. We also grouped kangaroo and goanna detections at the genus level due to the limited number of recordings at the species level. These species were most likely absent from plots as opposed to being misidentified or overlooked due to low rates of detection. Power to detect decreasing occupancy trends in these species with 2-ha-plot surveys will therefore be low unless an extremely large number of plots is established. Alternatively, if this level of survey effort is not feasible, then alternative survey approaches should be considered for those species that are more sensitive to population change, such as abundance or activity measures derived from live or camera trapping. For example, malleefowl are being successfully monitored across their distribution with a high level of power by recording the number of active nesting mounds, with sites carefully selected to encompass a range of habitat and management regimes (Benshemesh et al., 2018, 2020).

Further considerations

Our analysis highlighted key considerations for the implementation of a regional or national 2-ha-plot monitoring program. First, the rate of false positives will affect inferences about occupancy trends. We expect the rate of false positives to be relatively low in our data set since most of the 2-ha-plot data used here were collected by six to eight skilled and highly trained field ecologists. However, ensuring observers are adequately trained in the monitoring method and protocol is crucial to the successful implementation of a future 2-ha-plot monitoring program. Second, even if species were identified correctly, there were inconsistencies in our data set in how species were recorded. We attempted to reduce this source of error by screening species names, grouping or separating species if necessary (such as dusky hopping mouse); however, this was not always possible. This is potentially a major source of data loss if individuals or groups monitor 2-ha plots without a standardized protocol and data screening. Finally, we did not specify the exact location to establish new monitoring sites; rather, we used Zonation to identify regions that maximize power. The exact placement of sites within the top 10% of the study area will likely depend on logistical constraints and alternative monitoring objectives across organizations. For example, we assumed that the goal of monitoring was to detect trends in occupancy, but sites could be further stratified across vegetation types or fire histories within these regions to answer local questions about the influence of threats or about management effectiveness.

CONCLUSION

We provide a simulation framework that can inform decisions about where, when, and how to conduct a monitoring program to maximize power to detect changes in species distributions. Using this framework, we demonstrated that 2-ha-plot surveys were suitable for monitoring species with either large or limited distributions in Australia's deserts, as long as their sign was readily identified and they were detected frequently enough. However, the type of distribution, the rarity/commonness of signs, and the monitoring objective including the target species are critical for determining the best monitoring design. For our study area, surveying approximately 200 existing plots resulted in a high power to detect regional trends of 50% declines in occupancy for 10 of the 11 species modeled, covering introduced species and native species with large and restricted distributions.

Our simulation framework tool is flexible enough to accommodate either decreasing or increasing occupancy trends for multiple species. Although we presented one case study, our framework could be used in a range of ecological settings, including terrestrial and marine ecosystems where the aim is to detect trends in occupancy over time. A key requirement is sufficient presence–absence data to fit SDMs and predict species occupancy across a region of interest. If such maps or estimates are not available, habitat suitability indices could be developed using expert opinion, which could then be updated over time as data become available. We also simulated linear trends in occupancy over time across a range of plausible scenarios. Our framework could be extended to include more complicated range dynamics, such as contractions, expansions, or shifts due to climate change. Finally, we modeled trends in occupancy rather than trends in abundance over time. We therefore assumed a 1:1 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. An important area of future research is to expand the framework so that it can estimate power to detect changes in both occupancy and abundance/density data. Incorporating spatially explicit power analysis into conservation planning will result in more robust monitoring and, ultimately, lead to more confident and faster detection and reporting of population changes when they occur.

ACKNOWLEDGMENTS

This study was supported by funding from the Australian Government's National Environmental Science Program through the Threatened Species Recovery Hub. The surveys conducted by the SA Arid Lands Natural Resource Management (NRM) Board and AW NRM Board were funded through Australian Government Caring for Our Country, National Landcare Program grants, and the Government of South Australia. Surveys on Kalamurina Sanctuary were funded by supporters of the Australian Wildlife Conservancy. Surveys for the APY Lands sites were funded by the Jill Landsberg Trust and Holsworth Wildlife Research Endowment, administered by the Ecological Society of Australia, and by APY Land Management. For their survey efforts and project support we thank Oak Valley Rangers and Ben Deslanders; Joe Benshemesh; Jeff Foulkes; Pip Mawby (Walalkara rangers); Kalka-Pipalyatjatjara Indigenous Protected Area (IPA) ranger team, and Katiti-Petermann IPA ranger team, including Yangi-Yangi Fox, Sandra Petermann, Ankelia Nelson, Ashely Paddy, Tony Paddy, Emily Paddy, Nyanu Watson, Tenisha Fox, Tracey Guest, Sara Weir, Clyde Jochheim, Liane Wendt, and other members of the 2018 APY Biological resurvey team. Open access publishing facilitated by The University of Melbourne, as part of the Wiley - The University of Melbourne agreement via the Council of Australian University Librarians.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All code (dsouthwell, 2022) to support this research is provided in Zenodo at https://doi.org/10.5281/zenodo.6894901. Data supporting this research (including the repeat detection data used in Appendix S3) are sensitive and not available publicly. Data are available to qualified researchers from the relevant government and nongovernment data providers under various data licensing agreements. Details on the data providers are available in Appendix S8.

ORCID

Naomi Indigo https://orcid.org/0000-0002-0465-7849
Katherine Tuft https://orcid.org/0000-0002-3585-444X
Damaris Zurell https://orcid.org/0000-0002-4628-3558
Sarah Legge https://orcid.org/0000-0001-6968-2781

REFERENCES

Akaike, H. 1973. "Information Theory as an Extension of the Maximum Likelihood Principle." In *Second International Symposium on Information Theory* 267–81. Budapest: Akademiai Kiado.

Allen, B. L., A. Fawcett, A. Anker, R. M. Engeman, A. Lisle, and L. K. P. Leung. 2018. "Environmental Effects Are Stronger than Human Effects on Mammalian Predator–Prey Relationships in Arid Australian Ecosystems." *Science of the Total Environment* 610: 451–61.

Allen, B. L., and P. J. S. Fleming. 2012. "Reintroducing the Dingo: The Risk of Dingo Predation to Threatened Vertebrates of Western New South Wales." *Wildlife Research* 39: 35–50.

Allen, L., R. Engeman, and H. Krupa. 1996. "Evaluation of Three Relative Abundance Indices for Assessing Dingo Populations." *Wildlife Research* 23: 197–206.

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: e87291.

Araujo, M. B., and M. New. 2007. "Ensemble Forecasting of Species Distributions." *Trends in Ecology & Evolution* 22: 42–7.

Benshemesh, J., D. Southwell, R. Barker, and M. McCarthy. 2020. "Citizen Scientists Reveal Nationwide Trends and Drivers in the Breeding Activity of a Threatened Bird, the Malleefowl (*Leipoa ocellata*)." *Biological Conservation* 246: 108573.

Benshemesh, J., D. Southwell, J. Lahoz-Monfort, C. Hauser, L. Rumpff, M. Bode, T. Burnard, and B. I. E. Wintle. 2018. *Citizen Science and Database Management*. Melbourne: CSIRO Publishing.

Burbidge, A. A., and N. L. McKenzie. 1989. "Patterns in the Modern Decline of Western Australia Vertebrate Fauna: Causes and Conservation Implications." *Biological Conservation* 50: 143–98.

Cabeza, M., M. B. Araujo, R. J. Wilson, C. D. Thomas, M. J. R. Cowley, and A. Moilanen. 2004. "Combining Probabilities of Occurrence with Spatial Reserve Design." *Journal of Applied Ecology* 41: 252–62.

Caughley, G. 1977. *Analysis of Vertebrate Populations*. New York, NY: Wiley.

Di Cola, V., O. Broennimann, B. Petitpierre, F. T. Breiner, M. D'Amen, C. Randin, R. Engler, et al. 2017. "Ecospat: An R Package to Support Spatial Analyses and Modeling of Species Niches and Distributions." *Ecography* 40: 774–87.

Dickman, C., A. Greenville, and G. Wardle. 2018. In *Determining Trends in Irruptive Desert Species*, edited by S. Legge, D. Lindenmayer, N. Robinson, B. Scheele, D. Southwell, and B. Wintle. Melbourne: Monitoring Threatened Species and Ecological Communities CSIRO Publishing.

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carre, J. R. G. Marquez, et al. 2013. "Collinearity: A Review of Methods to Deal with It and a Simulation Study Evaluating their Performance." *Ecography* 36: 27–46.

dsouthwell. 2022. "dsouthwell/Aridzone: v1.0.0 (v1.0.0)." Zenodo. https://doi.org/10.5281/zenodo.689490e1.

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 *Monitoring Threatened Species and Ecological Communities*, edited by S. Legge, D. Lindenmayer, N. Robinson, B. Scheele, D. Southwell, and B. Wintle. Melbourne: CSIRO Publishing.

Elith, J., J. R. Leathwick, and T. Hastie. 2008. "A Working Guide to Boosted Regression Trees." *Journal of Animal Ecology* 77: 802–13.

Engeman, R. M. 2005. "Indexing Principles and a Widely Applicable Paradigm for Indexing Animal Populations." *Wildlife Research* 32: 203–10.

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: 473–82.

Freeman, E. A., and G. Moisen. 2008. "PresenceAbsence: An R Package for Presence Absence Analysis." *Journal of Statistical Software* 23: 1–31.

Garrard, G. E., M. A. McCarthy, N. S. G. Williams, S. A. Bekessy, and B. A. Wintle. 2013. "A General Model of Detectability Using Species Traits." *Methods in Ecology and Evolution* 4: 45–52.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. "Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone." *Remote Sensing of Environment* 202: 18–27.

Harrell, F. E. 2001. *Regression Modeling Strategies: With Application to Linear Models, Logistic Regression, and Survival Analysis*, 1st ed. New York, NY: Springer.

Hijmans, R. J., S. Phillips, J. Leathwick, and J. Elith. 2011. "Package 'dismo'." http://cran.r-project.org/web/packages/dismo/index.html.

Hijmans, R. J., and J. van Etten. 2012. raster: Geographic Analysis and Modelling with Raster Data. http://CRAN.R-project.org/package=raster.

Johnson, J. B., and K. S. Omland. 2004. "Model Selection in Ecology and Evolution." *Trends in Ecology & Evolution* 19: 101–8.

Jones, D. A., W. Wang, and R. Fawcett. 2009. "High-Quality Spatial Climate Data-Sets for Australia." *Australian Meteorological and Oceanographic Journal* 58: 233–48.

Legge, S., B. P. Murphy, H. McGregor, J. C. Z. Woinarski, J. Augusteyn, G. Ballard, M. Baseler, et al. 2017. "Enumerating a Continental-Scale Threat: How Many Feral Cats Are in Australia?" *Biological Conservation* 206: 293–303.

Lehtomaki, J., and A. Moilanen. 2013. "Methods and Workflow for Spatial Conservation Prioritization Using Zonation." *Environmental Modelling & Software* 47: 128–37.

Letnic, M., and C. R. Dickman. 2006. "Boom Means Bust: Interactions between the El Nino/Southern Oscillation (ENSO), Rainfall and the Processes Threatening Mammal Species in Arid Australia." *Biodiversity and Conservation* 15: 3847–80.

Letnic, M., and C. R. Dickman. 2010. "Resource Pulses and Mammalian Dynamics: Conceptual Models for Hummock Grasslands and Other Australian Desert Habitats." *Biological Reviews* 85: 501–21.

Liaw, A., and M. Wiener. 2002. "Classification and Regression by Random Forest." *R News* 2: 18–22.

Lindenmayer, D., J. Woinarski, S. Legge, D. Southwell, T. Lavery, N. Robinson, B. Scheele, and B. Wintle. 2020. "A Checklist of Attributes for Effective Monitoring of Threatened Species and Threatened Ecosystems." *Journal of Environmental Management* 262: 110312.

Lindenmayer, D. B., and G. E. Likens. 2018. *Effective Ecological Monitoring*. Melbourne: CSIRO Publishing.

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: 2248–55.

Mackenzie, D. I., and J. A. Royle. 2005. "Designing Occupancy Studies: General Advice and Allocating Survey Effort." *Journal of Applied Ecology* 42: 1105–14.

McDonald, P. J., G. W. Luck, C. R. Dickman, S. J. Ward, and M. S. Crowther. 2015. "Using Multiple-Source Occurrence Data to Identify Patterns and Drivers of Decline in Arid-Dwelling Australian Marsupials." *Ecography* 38: 1090–100.

McDonald-Madden, E., P. W. J. Baxter, R. A. Fuller, T. G. Martin, E. T. Game, J. Montambault, and H. P. Possingham. 2010. "Monitoring Does Not Always Count." *Trends in Ecology & Evolution* 25: 547–50.

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: e12591.

Morton, S. R., D. M. S. Smith, C. R. Dickman, D. L. Dunkerley, M. H. Friedel, R. R. J. McAllister, J. R. W. Reid, et al. 2011. "A Fresh Framework for the Ecology of Arid Australia." *Journal of Arid Environments* 75: 313–29.

Moseby, K., T. Nano, and R. Southgate. 2009. *Tales in the Sand: A Guide to Idenitfying Australia Arid Zone Fauna Using Spoor and Other Signs*. South Australia: Ecological Horizons.

Moseby, K. E., R. Brandle, and M. Adams. 1999. "Distribution, Habitat and Conservation Status of the Rare Dusky Hopping-Mouse, *Notomys fuscus* (Rodentia: Muridae)." *Wildlife Research* 26: 479–94.

Moseby, K. E., H. McGregor, B. M. Hill, and J. L. Read. 2020. "Exploring the Internal and External Wildlife Gradients Created by Conservation Fences." *Conservation Biology* 34: 220–31.

Pearce, J., and S. Ferrier. 2000. "An Evaluation of Alternative Algorithms for Fitting Species Distribution Models Using Logistic Regression." *Ecological Modelling* 128: 127–47.

Pedler, R. D., R. Brandle, J. L. Read, R. Southgate, P. Bird, and K. E. Moseby. 2016. "Rabbit Biocontrol and Landscape-Scale Recovery of Threatened Desert Mammals." *Conservation Biology* 30: 774–82.

Possingham, H. P., B. A. Wintle, R. A. Fuller, and L. N. Joseph. 2012. "The Conservation Return on Investment from Ecological Monitoring." In *Making Biodiversity Monitoring Happen in Australia*, edited by D. B. Lindenmayer and P. Gibbons, 49–61. Melbourne: CSIRO Publishing.

R Development Core Team. 2014. *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Roy-Dufresne, E., F. Saltre, B. D. Cooke, C. Mellin, G. Mutze, T. Cox, and D. A. Fordham. 2019. "Modeling the Distribution of a Wide-Ranging Invasive Species Using the Sampling Efforts of Expert and Citizen Scientists." *Ecology and Evolution* 9: 11053–63.

Skroblin, A., T. Carboon, G. Bidu, N. Chapman, M. Miller, K. Taylor, W. Taylor, E. T. Game, and B. A. Wintle. 2019. "Including Indigenous Knowledge in Species Distribution Modeling for Increased Ecological Insights." *Conservation Biology* 35: 587–97.

Southgate, R., and K. Moseby. 2008. "Track-Based Monitoring for the Deserts and Rangelands of Australia." Envisage Environmental Services Ecological Horizons.

Southgate, R., R. Paltridge, P. Masters, and S. Carthew. 2007. "Bilby Distribution and Fire: A Test of Alternative Models of Habitat Suitability in the Tanami Desert, Australia." *Ecography* 30: 759–76.

Southgate, R., R. Paltridge, P. Masters, and T. Nano. 2005. "An Evaluation of Transect, Plot and Aerial Survey Techniques to Monitor the Spatial Pattern and Status of the Bilby (*Macrotis lagotis*) in the Tanami Desert." *Wildlife Research* 32: 43–52.

Southgate, R., A. Skroblin, D. Southwell, and S. Legge. unpublished. Influences on Detectability During Track-Based Surveys in Arid Australia.

Southwell, D., L. Einoder, J. Lahoz-Monfort, G. Gillespie, A. Fisher, and B. Wintle. 2019. "Spatially Explicit Power Analysis for Detecting Occupancy Trends in Multiple Species in Dynamic Landscapes." *Ecological Applications* 29: e01950.

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: e01950.

Stafford Smith, D. M., and S. R. Morton. 1990. "A Framework for the Ecology of Arid Australia." *Journal of Arid Environments* 18: 255–78.

Stanley, T. R., and J. A. Royle. 2005. "Estimating Site Occupancy and Abundance Using Indirect Detection Indices." *Journal of Wildlife Management* 69: 874–83.

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.

Taylor, B. L., M. Martinez, T. Gerrodette, J. Barlow, and Y. N. Hrovat. 2007. "Lessons from Monitoring Trends in Abundance of Marine Mammals." *Marine Mammal Science* 23: 157–75.

Woinarski, J. C., A. A. Burbidge, and P. L. Harrison. 2014. *The Action Plan for Australian Mammals 2012*. Collingwood: CSIRO Publishing.

Yang, L. H., K. F. Edwards, J. E. Byrnes, J. L. Bastow, A. N. Wright, and K. O. Spence. 2010. "A Meta-Analysis of Resource Pulse-Consumer Interactions." *Ecological Monographs* 80: 125–51.

Yoccoz, N. G., J. D. Nichols, and T. Boulinier. 2001. "Monitoring of Biological Diversity in Space and Time." *Trends in Ecology & Evolution* 16: 446–53.

Young, A. R., K. E. Selwood, J. Benshemesh, J. Wright, and D. Southwell. 2022. "Remotely Sensed Vegetation Productivity Predicts Breeding Activity and Drought Refuges for a Threatened Bird in Semi-Arid Australia." *Animal Conservation* 15: 28–53.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Southwell, Darren, Anja Skroblin, Katherine Moseby, Richard Southgate, Naomi Indigo, Brett Backhouse, Keith Bellchambers, et al. 2022. "Designing a Large-Scale Track-Based Monitoring Program to Detect Changes in Species Distributions in Arid Australia." *Ecological Applications* e2762. https://doi.org/10.1002/eap.2762