Animal Conservation. Print ISSN 1367-9430

Designing fit-for-purpose monitoring – A case study of a cryptic songbird

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Keywords
effective monitoring; population monitoring; adaptive management; conservation planning; practical conservation guide; applied conservation; threatened species.

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Editor: Rahel Sollmann
Associate Editor: Jennifer Moore

Received 18 June 2023; accepted 02 October 2024

doi:10.1111/acv.12995

Abstract

Monitoring threatened species is essential for understanding their conservation needs and developing effective recovery strategies. However, designing and implementing monitoring programs can be challenging in resource-constrained environments, where conservation practitioners must balance the need for detailed information with limited resources. We present a case study focusing on the design of a range-wide monitoring program for the Endangered rufous scrub-bird (*Atrichornis rufescens*) in the mountain forests of eastern Australia. We first developed a 'wish list' of monitoring questions and then trialed the methods needed for answering them using sequence of pilot studies. We implemented a phased approach comprising (i) a study of whether individuals could be identified by their songs, (ii) identification of a 'core range' using species distribution models to refine the search area, and (iii) a trial of the efficacy of a preferred feasible monitoring approach. We offer a practical pathway for designing question-driven monitoring programs for threatened species. Our study highlights the importance of clarifying explicit monitoring goals and tailoring methods to suit species' ecological and life history characteristics. By following this systematic approach, conservation efforts can obtain valuable information for effective management, even with limited resources and prevailing uncertainty about species ecology.

Introduction

Monitoring of threatened species to understand their population dynamics is a first step in understanding how to help recover them (Robinson *et al*., 2018). However, the design and implementation of monitoring programs is typically undertaken in resource constrained environments, with only limited funding available for even urgently needed programs (Wintle *et al*., 2019). Thus, conservation practitioners must balance the need for detailed information against the practical limitations of financial, personnel and logistic constraints (Scheele *et al*., 2018). Moreover, the rarity and behavior of the target species will influence the methods used and type of data that can be collected. The balance between an achievable vs. an ideal monitoring project must be struck. Sufficient information must be obtained to serve the needs of conservation practitioners (Canessa *et al*., 2015), without seeking so much information that monitoring becomes cumbersome and difficult to sustain (Likens & Lindenmayer, 2018). Thus, before embarking on designing and implementing a large-scale project, practitioners typically benefit from small-scale pilot studies that evaluate tools and techniques so that the scope of monitoring can be narrowed to aims that are both achievable and useful.

Fundamental to selecting a monitoring approach is to decide what kind of information is needed (Himes Boor Gina, 2013). Biodiversity monitoring can collect a wide variety of information, often involving data needed to make conservation assessments (IUCN, 2012). Important information that can be collected includes death (Stojanovic *et al*., 2020) and birth rates (McLennan *et al*., 2018), distribution over space (Webb *et al*., 2014), impacts of stochastic events (Crates *et al*., 2021), population density and size (Alves *et al*., 2019), temporal population change (Lindenmayer & Sato, 2018; Nicoll *et al*., 2021), genetic traits (Stansbury Carisa *et al*., 2014) and behavior (Grueber *et al*., 2017). Given the potentially bewildering array of questions and techniques faced by conservation practitioners at the outset of project planning, where should one begin? The answer to this question will vary between species and contexts, such that different approaches may need to be adapted or combined to gather the information needed for effective conservation management. In the first instance, conservation managers could develop a prioritized 'wish list' of monitoring questions. It will naturally be impossible to answer every question for every species and wish lists may quickly be whittled down based on feasibility and cost-effectiveness, and priorities may change over time. Feasibility and cost-effectiveness are critical, but often difficult to assess, especially for understudied species with limited existing ecological information to guide planning. In these cases, a sequence of pilot studies may need to be implemented to evaluate the feasibility of answering different questions. Thus, before any monitoring even takes place, practitioners may need to have already implemented multiple smaller-scale trials to test techniques and rule out questions that are infeasible to answer.

In this context, we present a case study evaluating potential monitoring approaches for an Endangered songbird. Rufous scrub-birds *Atrichornis rufescens* are a cryptic skulking endemic of the dense undergrowth of mountain rainforests of the east coast of Australia (Higgins *et al*., 2001). The species is at risk of extinction from global heating, wildfires and retreat/loss of their preferred elevation niche (Department of the Environment, 2014). There have been some previous efforts to study the species (Supplement 1, Literature summary), but there has not yet been a methodologically consistent approach to undertaking a range-wide study of their ecology, status and conservation intervention needs. This is because (in addition to lack of resourcing) the cryptic behavior of rufous scrub-birds resists direct observation and routine capture, and their preferred habitat comprises extremely difficult terrain for surveys (mountain slopes with thick scrubby vegetation) (Higgins *et al*., 2001). Consequently, little information is available for evaluating their contemporary status and future population viability. Establishing range-wide monitoring protocols for the species has been identified as a high conservation priority (Department of the Environment, 2014), but has been hindered by uncertainty about feasibility. Apart from the difficulty of physically traversing the terrain inhabited by rufous scrub-birds, the species occurs in scattered populations along >450 km of latitude over the east Australian Great Dividing Range. Despite these difficulties, we aimed to devise a cohesive, range-wide monitoring effort for the species.

We first identify a 'wish list' of critical questions identified by conservation practitioners to inform the management of rufous scrub-birds. Then, after identifying a 'core search area' using species distribution models, we implement a series of pilot studies to evaluate the feasibility of different approaches based on the species' ecology. By combining generalizable monitoring program design principles (Stojanovic *et al*., 2021) with approaches tailored to the quirks of rufous scrub-birds, we identify a subset of feasible monitoring questions that can be answered at a manageable cost. Our study offers a template for conservation practitioners seeking to create monitoring programs in the context of entrenched uncertainty about a species.

Materials and methods

Study species

Rufous scrub-birds are known from just five areas of northern New South Wales (NSW) and southern Queensland (QLD) (Higgins *et al*., 2001). They are brown, small, and prefer foraging and nesting in low, dense vegetation near high-elevation rainforests (Department of the Environment, 2014). Although not well studied, available evidence suggests that the species has a territory size of 0.5–1.7 ha (Stuart, 2018), but research techniques that require more intensive study are limited by the logistic challenges of capturing them (Kyte & Stuart, 2022). Rufous scrub-birds have extremely loud and distinguishable songs, making them detectable during the breeding season (Newman & Stuart, 2011). Female rufous scrub-birds are widely believed to be less detectible by song (Newman & Stuart, 2011), but the evidence for this is relatively weak. Singers have a large repertoire that includes mimicry and a number of species-specific calls (Stuart & O'Leary, 2019). Rufous scrub-birds forage on the ground for invertebrates and lay two eggs in nests hidden in the forest understory (Higgins *et al*., 2001) but there remains major uncertainty about other aspects of their ecology and life history. There have been several previous studies of scrub-birds, but these efforts have had several important limitations that hindered inference (e.g. biased survey effort to known areas of scrub-bird occupancy, inconsistent survey methods, and unclear monitoring goals – see Supplement 1).

Monitoring 'wish list' and project design rationale

There is no range-wide information about the species' demographic trends, population size and density over space and time. This project focused on achieving a survey design that could explicitly address knowledge gaps at a range-wide scale, in the hope that future resources may be found to implement a national monitoring program. We define rufous scrub-bird monitoring as an effort to establish a relationship between some meaningful demographic indicator and space × time. We hoped also to create a monitoring framework that could facilitate new research into more targeted aspects of life history and the species' conservation needs. We envisaged that this would be achieved by gathering information about the location and extent of scrub-bird populations to facilitate further study. In the absence of a recovery team, consultation with species experts identified the following questions:

1. Where does the species occur?
2. What is the size of each population?
3. What is the trajectory of each population?
4. How do habitat preferences vary over space and time?
5. Does population density vary with habitat suitability?
6. What is the reproductive success of the species over space and time?

7 How will we know if recovery efforts are successful in the future?

This wish list comprises three data types (listing in increasing order of resolution and decreasing order of perceived feasibility): (i) presence/absence – questions one, three, four and seven; (ii) abundance/density – questions one through five and seven; and (iii) demographic – question six and seven. Based on this list, abundance/density approaches address the largest number of questions in the wish list, with a moderate level of resolution and feasibility relative to the other data types. Thus, abundance/density-based approaches were our highest priority as a starting point. Demographic data (question six) are high value but unfeasible on a large scale given the species' cryptic behavior and challenging terrain of their habitat – thus we ruled out question six at the outset. We considered presence/absence data (questions one, three, four and seven) to be the most feasible but least informative data type, and thus we treated them as a back-up if the outcomes of the pilot studies indicated that preferred abundance/density options were unfeasible (see below). Importantly, given that rufous scrub-birds are spread over a very large geographic area of challenging terrain, there is major uncertainty about the spatial extent and occurrence of suitable habitat (question one) so we opted to use species distribution models to refine and define the spatial extent of a 'core range' as a starting point for our pilot studies and any future monitoring (below).

Given abundance/density data were informative and potentially feasible, we initially focused on the methods associated with these data. There are several approaches for deriving abundance/density data that are well-developed for birds with strong statistical foundations and clear assumptions. One key consideration that we used as a means of ruling different methods in or out was that whilst it is possible to capture rufous scrub-birds (Kyte & Stuart, 2022), it is unlikely that they could be caught at a rate needed to inform capture-recapture models (Pradel, 1996). Likewise, we ruled out non-invasive mark-recapture techniques using genetic samples from traces such as droppings or shed feathers (Petit & Valiere, 2006; Puechmaille & Petit, 2007) because the probability of encountering these traces in the field was deemed negligible.

We considered whether distance sampling (Buckland *et al*., 2004, 2006) might be feasible as a survey approach for gathering abundance/density data. Scrub-bird songs can be heard from afar, however, distance sampling requires precise estimation of the distance of animals from observers (Buckland *et al*., 2004). Accurate estimation of distance was deemed difficult because rufous scrub-birds are (i) too cryptic to visually observe with regularity, making accurate estimation of distance unlikely, (ii) so loud that even relatively distant individuals may be mistaken as nearer than they actually are and (iii) rugged terrain makes estimation of distance challenging. Furthermore, the species is considered capable of ventriloquism adding further complexity to accurate distance estimation even at close range (Higgins *et al*., 2001). Thus, we ruled out distance sampling as a range-wide monitoring approach from the outset, noting that this choice traded off resolution and additional information (offered by distance sampling) for feasibility (offered by occupancy approaches).

Pilot study 1 – using male song to identify individuals

Given scrub-birds sing loudly, if individuals could be distinguished based on differences in the features of their songs, mark-recapture techniques could be used to calculate the densities of singers. However, in related noisy scrub-birds *A. clamosus*, there were insufficient differences among individuals to confidently discriminate between individuals on call characteristics (Portelli, 2004). Nevertheless, given the potential value of the abundance/density information for achieving our wish list (and the limited alternative options for gathering this information), we decided to test if rufous scrub-birds could be identified from song.

Data collection – All calls were collected from the Gloucester Tops area of Barrington Tops National Park (−32.0359; 151.3536) by AS in January and February 2020. Many of the territories in this area are well-known and have been the subject of previous studies (Newman & Stuart, 2011). Chip calls were the dominant call recorded being present on more than 70% of the 95 sound files. We are confident that all calls are from unique individuals because the calls were recorded within a short time window at known occupied territories of singing rufous scrub-birds.

Call classification and statistical analysis – Spectrograms were scanned and chip calls were extracted using Raven Lite version 2.0.1 (K. Lisa Yang Center for Conservation Bioacoustics at the Cornell Lab of Ornithology, 2023). Only calls with minimal background noise such as other species vocalizing and movement of vegetation were used, resulting in 408 caLL phrases from 15 individuals (differentiated based on singing territory locations). We only used phrases that consisted of two or more syllables and separated these into upward- or downward-inflected phrases. We describe the calls of scrub-birds (Fig. 1) following Ferrier (1984):

1 Syllable – a sound continuous in time (i.e. the smallest 'unit' of a song)
2 Phrase – a sequence of syllables
3 Bout – a sequence of song in which a phrase of chipping is repeated at regular intervals.
4 Inflection of syllables – each phrase was classified according to whether it involved upward- or downward-inflected syllables.

All data analysis was performed in R version 4.3.3 (R Development Core Team, 2023). Forward and backward sloping chip calls were considered separately after we confirmed that individuals could produce both types of calls. We imported the trimmed .wav files of sufficient quality into R using the package *warbleR* version 1.1.26 (Araya-Salas & Smith-Vidaurre, 2017). Individuals with less than four

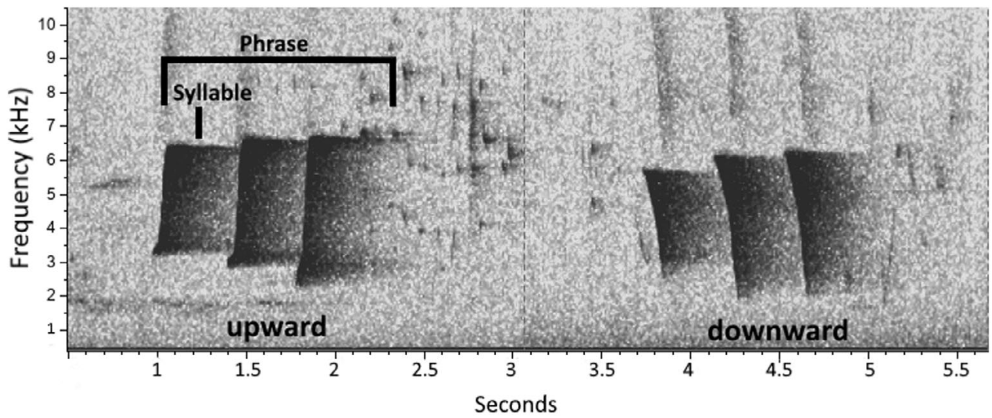

Figure 1 Spectrogram of chip calls from a single recording of a singing rufous scrub bird. The difference between a syllable and a phrase is illustrated. We used this call type in our analysis to trial whether it is possible to differentiate between individual singers. Both the upward and downward inflected calls were included in the analysis, but separate analyses were performed for each inflection

phrases in our data were removed from the analysis because such a low sample hindered the analysis. After filtering, we were left with (i) downward chip calls: $n = 272$ phrases from 10 individuals and (ii) upward chip calls: $n = 128$ phrases from eight individuals. Some individual scrub-birds appear in both the downward and upward chip call datasets, whereas others appear only in one.

After restricting the frequency range to 1.5–8 kHz, we manually selected the start and end coordinates of each song, using the functions *sig2noise* to increase the signal-to-noise ratio (type = 3) and *trackfreqs* to identify the spectral components of each spectrogram. We visually inspected spectrograms to ensure track frequency selections were representative of the spectral components of each song and used function *specan* to quantify 27 spectral attributes of each song. We checked for pairwise correlation across all attributes using *GGally* version 1.4.0 (Schloerke *et al*., 2022) and removed attributes that showed consistent strong correlations with other attributes ($R > 0.8$). Using boxplots, we visually assessed the distribution of the remaining variables. We preferred this approach to performing an analysis of variance so we could assess the variation for each attribute within, rather than between, individuals. Using these boxplots we accepted, rejected or log-transformed variables to fulfill normality assumptions, resulting in 15 variables listed in Supplement 1, Table S1, that were included in downstream analyses.

To test the combination of acoustic characters together, we generated principal components analyses in package *MASS* version 7.3 (Venables & Ripley, 2002) using these 15 acoustic variables. We generated principal components separately for the chip calls that were downward and upward inflected. We used the scores from the acoustic variables as the predicators and the identity of each individual bird as the response variable. We retained all principal component scores with eigenvalues greater than one.

We then used linear discriminant analysis using the 'lda' function in *MASS* version 7.3 (Venables & Ripley, 2002) to test the automated assignment of calls to individual birds based on the principal components from both the downward- and upward-inflected chip calls. We assessed the classification success of the linear discriminant analysis by splitting the data (for each call type, from each individual bird) into training (80%) and test (20%) data sets.

Pilot study 2 – identifying the core range and evaluating detectability of scrub-birds in a systematic monitoring framework

Identifying the core range – Before trialing pilot studies of potential monitoring methods in the field, we aimed to refine the search area by identifying a 'core range'. Species distribution modeling (SDM) is a technique widely used in ecology and conservation to predict the probability of occurrence of the target species using multiple environmental predictors and a series of modeling techniques (Franklin, 2010). SDMs are crucial to support conservation decision-making (Guisan *et al*., 2013), and can even help to identify new populations of species when field validation is undertaken to confirm model predictions (e.g. Del-Rio *et al*., 2015). When fitting SDMs, spatial thinning is often employed to mitigate occurrence bias, such as over-sampling in certain areas. However, spatial thinning cannot correct the data for areas that have not been sampled at all. Moreover, locally dense records may accurately represent the true suitability of the habitat. Given that the objective of our model was to inform the design of a stratified survey, we chose not to apply spatial thinning. In doing so, we acknowledged the need to collect data in future surveys that will enable us to build a more robust species distribution model.

We downloaded occurrence records for rufous scrub-birds from the Atlas of Living Australia (https://www.ala.org.au/). Data were cleaned to ensure records were recent (i.e. since 2000) and accurate (i.e. spatial accuracy was <300 m). To define the study area, we obtained spatial vector data (i.e. shapefile) from BirdLife of the rufous scrub-bird's potential distribution (Birdlife International and Handbook of Birds of the World, 2020). Some points fell outside but near the boundary of the potential distribution; however, this boundary was simply used to define an area to predict and the shapefile is not authoritative. Therefore, we created a 50 km buffer around the potential distribution, increasing the area to also incorporate those occurrences outside Birdlife's polygon (Fig. 2a). SDMs can be built with several data types and sampling processes (Guillera-Arroita *et al.*, 2015). In the cases of species for which only occurrence data are available, modeling algorithms require additional data representing the range of environmental conditions in the modeled region, known as background points (Phillips *et al.*, 2009). Some of the algorithms used for modeling can be sensitive to the number of background points in relation to presences; therefore, we used a similar number of background points as available presence records (Barbet-Massin *et al.*, 2012). We created 600 random background points across the study area, and our final dataset comprises 1134 points: 534 occurrence records (after filtering) and 600 background points (Fig. 2a).

We used three types of variables for modeling: bioclimatic variables, resource and landscape variables (Supplement 2, Table S2). We based the selection of variables on the little information available on the ecology of rufous scrub-birds, and we also chose predictors that are known to be important for other forest bird species (e.g. Besnard *et al.*, 2013). Rainfall and humidity seem to be important for rufous scrub-birds (Higgins *et al.*, 2001); therefore among the bioclimatic variables, we chose predictors that may influence humidity (e.g. annual precipitation and precipitation of the driest month) and variables that describe seasonality and extreme or limiting climatic factors. Bioclimatic predictors were derived using a 250 m × 250 m resolution (i.e. raster cell size) digital elevation model (DEM) (Geoscience Australia, 2008) in ANUCLIM version 6.1 (Xu & Hutchinson, 2011). We also used the DEM to calculate the topographic predictors, aspect and slope, using the package 'terra' version 1.7 (Hijmans, 2021). We obtained the layer for topographic wetness index (TWI) from the CSIRO database (Kidd *et al.*, 2014) with a cell size of three arc seconds (90 m) and resampled to 250 m cell to align with the other rasters used

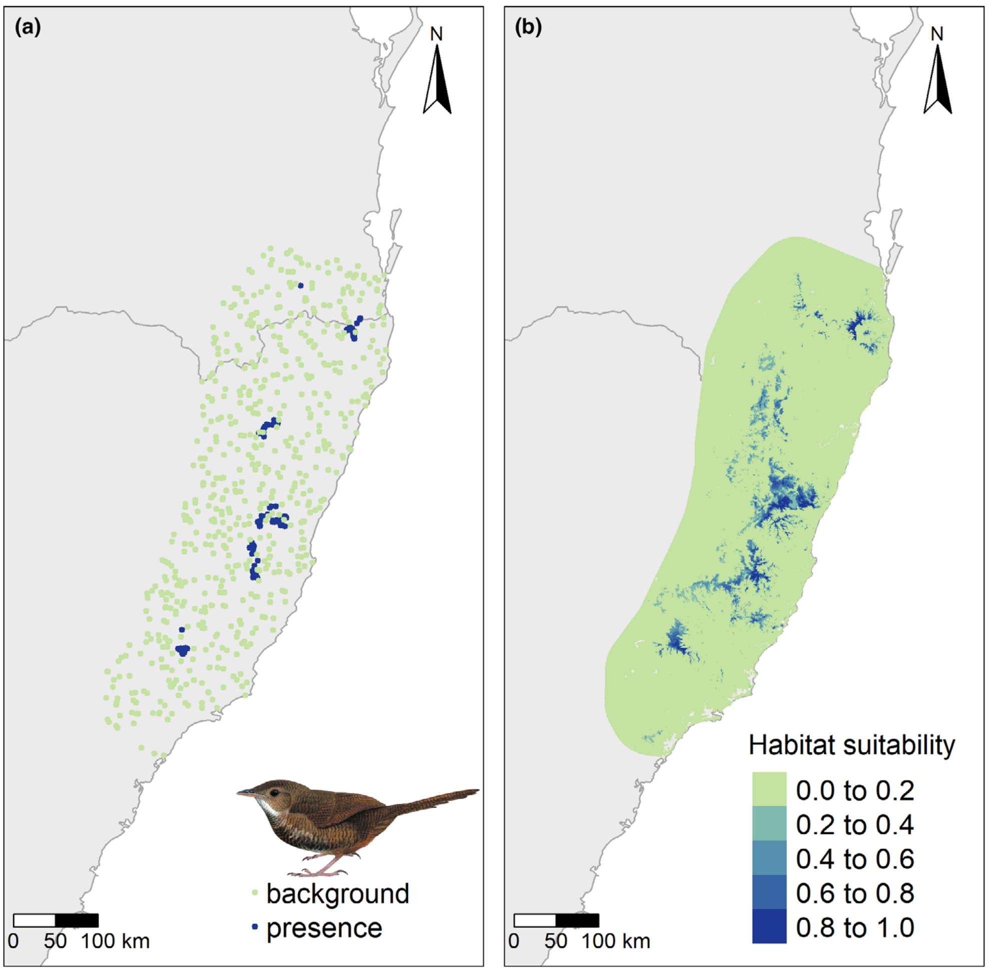

Figure 2 Presence data for rufous scrub birds across their entire geographic distribution and background data used for modeling (a); predicted relative habitat suitability distribution of rufous scrub-bird for the current climate (b). Image credit: Brian Small, © Lynx Edicions

for modeling. We downloaded the rivers layer from Geoscience Australia (Crossman & Li, 2015) and included distance to rivers as a predictor. Using the dynamic land cover layer (Lymburner *et al.*, 2015), we calculated the predictor proportion of closed forest. The 15 environmental variables selected for modeling are described in Supplement 2, Table S1, but not all variables were included in the models due to correlation between some predictors (see data analyses).

Correlated variables can lead to instability in parameter estimation (Dormann et al., 2013). Given that some SDM algorithms are sensitive to correlation, we first tested for correlation among variables using the variance inflation factor (VIF) (Zuur et al., 2010). VIF measures how strongly each predictor can be explained by the rest of predictors. Using the *vifstep* function, we removed predictors with VIF >10 (Chatterjee & Hadi, 2012) – variables included in the analyses are shown in Supplement 2, Table S1. We modeled the distribution of rufous scrub-birds using the package 'sdm' in R version 4.0.5 (Naimi & Araújo, 2016; R Core Team, 2021). The 'sdm' package enables several modeling algorithms to be fitted simultaneously and allows ensembles of models, which combines predictions across different modeling methods to generate a single spatial prediction. Using the sdm function, we fitted four models to the data: boosted regression tree (brt), random forest (rf), generalized linear model (GLM), and maxent, and conducted a model evaluation using a data-splitting method (Naimi & Araújo, 2016). We used random subsampling (sampling without replacement), which repeats the random data splitting into training (model fitting) and testing (model evaluation) proportions. We subsampled 30% of the data 10 times for model evaluation. We also assessed the predictive performance of models using the area under the receiver operating curve (AUC) (Fielding & Bell, 1997). Area under the receiver operating curve values near one represent models with good discriminatory ability, i.e. the model discriminates between presences and background points. To generate the spatial prediction, we performed a model ensemble based on a weighted averaging that is weighted using AUC statistic.

Evaluating detectability of scrub-birds in a systematic monitoring framework – based on the results of Pilot study one, we decided that abundance/density data were not feasible for scrub-birds. Thus, we opted to evaluate the feasibility of surveys in an occupancy monitoring framework to collect presence/absence data (MacKenzie *et al.*, 2006). This approach, whilst lower resolution than abundance/density approaches, has successfully been applied to other difficult species, i.e. those inhabiting large areas of challenging terrain that cannot readily be identified individually (Webb *et al.*, 2014; Stojanovic *et al.*, 2021). We aimed to evaluate the utility of the species distribution model (above) at predicting habitat suitability for the species. We designed the study with the intention of piloting approaches to answer the wish list questions one and four.

Study site and field data collection – We implemented the study at the Gloucester Tops area of Barrington Tops National Park (−32.0359 151.3536, Fig. 3) in September 2022 over eight days. We used the SDM for rufous scrub-birds developed in the previous step of this project as a basis for site selection. We divided the study area into three classes of predicted habitat suitability from the SDM, i.e., high (1–0.7), medium (0.69–0.5) and low (0.5–0). We excluded low-suitability sites from our survey and biased our sampling to favor high-suitability sites to improve the likelihood of collecting enough data to estimate detection probabilities. Sites were separated by at least 500 m (based on in situ trials of the distance from calling scrub-birds at which they could be detected confidently), and we only placed sites in areas where potential habitat occurred (i.e. forest, rainforest and the edges of woodland).

We used a survey protocol that traded-off site-level resolution for high spatial coverage of the study area. We did this because singing scrub birds are loud and persistent, so we assumed long surveys should not be needed to detect them if present. Surveys were up to 5 min duration and began with a 2 min listening period by the surveyor, followed by 1 min of intermittent song broadcast, and a further 2 min listening. We recorded the presence or absence of scrub-birds based on hearing their songs. Thus, we assume our detections are biased to male scrub-birds only. Detections were often made before the third minute of the survey. In those cases, we did not broadcast calls to reduce welfare impacts on singers, and surveys could be terminated early. Each site was surveyed at least twice, but we aimed to implement at least three surveys at every site in high suitability habitat. The average number of surveys per site was 3.6 (range: 2–5), and every site where scrub-birds were detected was surveyed at least three times (to improve estimates of detectability). Surveys were conducted only during good weather with low wind and no rain. Based on field observations of calling behavior at the time of the pilot study, we surveyed any time during daylight hours. At each site, we recorded a measure of vegetation clutter in the understory as an ordinal factor (low, medium and high) as this structural site-level trait was expected to potentially influence occupancy patterns of scrub-birds (i.e. we expected scrub-birds to prefer cluttered sites over open ones). Only one person recorded clutter for all sites to reduce observer bias.

Data Analysis – All data analysis was performed in R version 4.2.2 (R Development Core Team, 2023) using the package *unmarked* version 1.4.1 (Fiske & Chandler, 2011). We fitted three single-season occupancy models. The detection probability component (p) was held constant in each model. For the occupancy component (Ψ), we fitted a constant model and two other models that included the underlying SDM habitat suitability score of each site, and the clutter index collected from the field as fixed effects. We compared the three models based on ΔAIC (Burnham & Anderson, 2002).

Results

Pilot study 1

Principal components analysis of the downward- and upward-inflected chip calls supported the decision to separate these calls for all analyses, because these calls were highly differentiable with little overlap in the 50% ellipses (Supplement 1, Fig. S1). When analyzed separately, five principal components had an eigenvalue of >1 for downward chip calls and four for upward chip calls. In both cases, these principal components combined accounted for 76% of the variance in calls (Supplement 1, Table S2). We could not reliably discriminate individuals from either call. Linear discriminant analysis only yielded an overall predicted classification success of 47% (downward) and 76% (upward) for each call type based on the training dataset. Downward chip calls were assigned to the correct individual between 0 and 82% of the time (Supplement 1, Table S3). Upward chip calls performed better and were assigned correctly between 44 and 92% of the time (Supplement 1, Table S4). To test whether a few individuals with high variation in call traits explained this low performance of the linear discriminant analysis, we trialed removing these individuals from the analysis, but performance did not improve.

Pilot study 2

Identifying the core range – the most influential predictors of rufous scrub-bird habitat suitability were the maximum temperature of the warmest period (bio 05) and annual precipitation (bio 12). Overall, the suitability of rufous scrub-bird habitat decreased with increased temperature during the warmest period, and increased with higher annual precipitation (Supplement 2, Fig. S1). Forest cover was also an important predictor, particularly in the maxent model (Supplement 2, Fig. S1). Species data used for modeling and spatial predicted probability of rufous scrub-bird habitat suitability are presented in Fig. 2. Predictive performance was very good across the models (AUC: 0.99, Supplement 2, Table S3), with very high scores for observed presence records, and very low scores for background points with little overlap (uncertainty) between the two (Supplement 2, Fig. S2).

Evaluating detectability of scrub-birds – rufous scrub-birds were detected in 19/73 survey sites (Fig. 3). Based on ΔAIC <2 we found comparable support for the constant model and the one containing the effect of the SDM habitat suitability score on occupancy (Supplement 2, Table S4). We preferred the model with the SDM-based habitat suitability because it had the lowest AIC. From that model, we estimate that at occupied sites rufous scrub-birds had a detection probability of 0.49 ± 0.07se, and an overall occupancy probability of 0.34 ± 0.07se (95% confidence intervals: 0.22–0.50) in areas of high suitability habitat based on the SDM, and 0.12 ± 0.08 (CI: 0.30–0.37) in areas of medium suitability.

For a subset of 31 scrub-bird detections where the information was collected, 13 birds were detected before the call broadcast and 18 were detected after the call broadcast.

Evaluating our ability to answer the monitoring questions

We decided at the outset that our preferred approach would focus on methods that yield abundance/density-related data. The results of the first pilot suggest that approaches that rely on individual acoustic recognition to discriminate among individuals can be ruled out. The results of the second pilot also suggest that other methods that rely on surveyors on foot are unlikely to be suitable based on safety concerns alone. Given that the rufous scrub bird is likely to be monitored into the long term by citizen scientists and volunteers, we opted in the second pilot study to trial occupancy-based approaches from roads/tracks. This approach has major limitations, for example, surveys limited to the area within earshot of the few tracks traversing the study area are likely unrepresentative. Moreover, occupancy-based approaches provide no information about abundance or density, as required for many of our wish list questions. Based on the approaches we trialed, we are only able to answer two questions from our wish list, namely (Q1) where does the species occur, and (Q4) how do habitat preferences vary over space and time? To address these questions properly though, we would need to expand the spatial coverage of our survey area and implement the occupancy approach over a longer temporal scale. Importantly, our pilot studies provide a way forward for managers to search new regions identified as suitable based on the species distribution model, empowering them to search new areas for rufous scrub-birds. Furthermore, increasing the number of known occupied sites (with different habitats and terrain) may provide new opportunities to trial different methods and statistical techniques for addressing other wish lists of questions. For example, other approaches like eDNA, genetic capture-recapture and spatial capture-recapture techniques (Augustine *et al.*, 2019), may also be useful alternative methods for estimating density and abundance. Given that rufous scrub birds can be captured (Supplement 1), at locations where the terrain can be traversed it may be possible to gain more detailed local insights into population processes than occupancy approaches alone can offer. This in turn would address the other questions in our wish list that would otherwise go unanswered.

Discussion

Our approach in this study can be summarized as a sequence of actions: (i) identify the questions, (ii) narrow down the available methods to answer them, (iii) identify where the methods might be applied, (iv) trial the most promising approaches, (v) design a monitoring program. Depending on the outcome of the preceding steps, the direction taken may vary dramatically between species and places. We started with a wish list of monitoring questions identified in discussion with key stakeholders (state and local Governments, NGOs, research agencies and species experts). Abundance/density data were required to answer most wish list questions, so we prioritized methods that yielded this type of information. After ruling out distance sampling and capture-mark-recapture approaches on feasibility constraints, we tested our capacity to discriminate between singers on the basis of song characteristics (as a potential means of non-invasive capture-recapture). We found major overlap among singers in all song traits measured, ruling out both this method and abundance/density data for addressing the

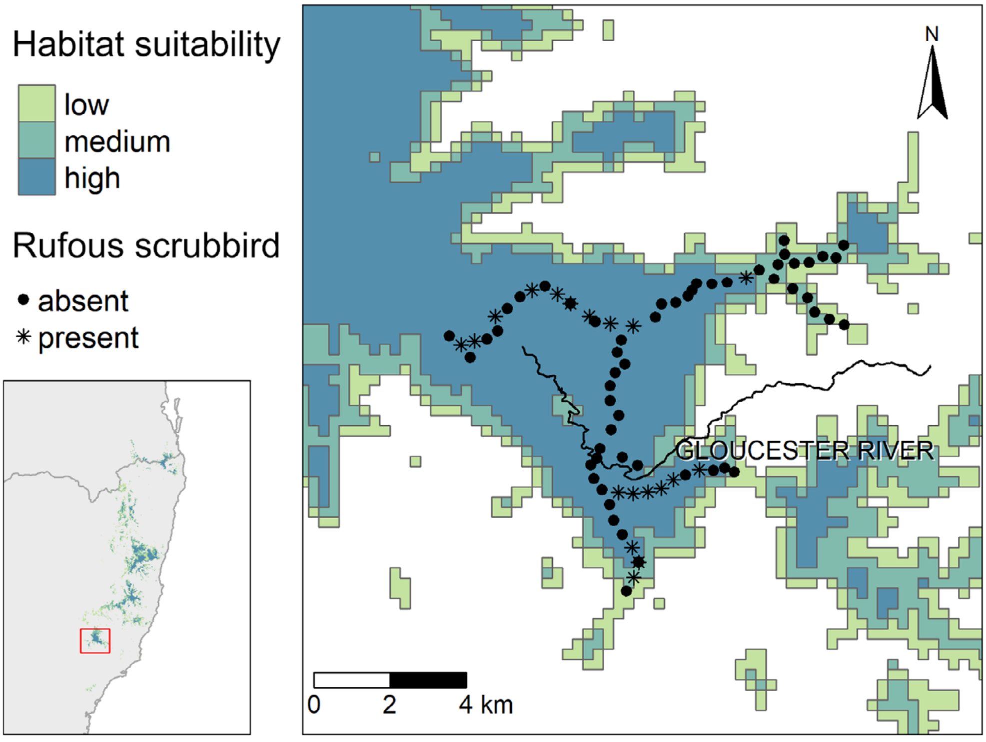

Figure 3 Study area map showing the predicted habitat suitability from the species distribution model (SDM) for rufous scrub birds in New South Wales from Fig. 2, and the surveyed sites in Barrington Tops National Park along with the occupied and unoccupied sites

wish list. We note though that deep learning and AI may provide new opportunities to revisit these questions in the future (Xie *et al*., 2023). Next, we used SDMs to refine and identify a core range of the species across its geographical distribution. We acknowledge that by not fully addressing potential biases in the occurrence data, the model output in turn may be biased. However, given that the model's primary purpose is to inform the design of a new survey, including areas of low suitability, we believe it remains fit for purpose. Our SDM identified multiple areas where surveys could be undertaken to confirm the occurrence of rufous scrub-bird and to establish monitoring sites beyond known hotspots of occurrence. Finally, we used the results of the SDM to select an area to implement a second pilot study aimed at collecting presence/absence data in an occupancy framework. Occupancy style surveys are relatively low-resolution because no individual level or density information can be derived. In rufous scrub-birds they are further biased to the detectible subset of the population, i.e. singers close to accessible areas. Nevertheless, we found that this approach was feasible, rapid, and could be applied at spatial scales large enough to yield useful conservation information. Based on pilot study two, we can be confident that the occupancy approaches used can be scaled-up across a larger area of the range. However, overcoming inherent biases in surveying only accessible areas remains an outstanding problem because the dense mountaintop forests where the species lives are extremely challenging to traverse off-track.

We conclude that occupancy-style surveys are an appropriate approach for setting up a monitoring program for rufous scrub-birds. The use of the SDM to guide selection was informative at the scale of the survey area and is a good starting point for implementing a larger, range-wide survey. This approach has been successful for other species with lower detection probabilities than those recorded here (Stojanovic *et al*., 2021). Using the SDM during the survey design phase may also enable us to explicitly test the accuracy of the model, enabling future updating and refinement of the SDM to improve its predictive capacity. This will empower further field surveys to discover new populations (Stojanovic *et al*., 2021). This is particularly important because we used presence-only data to fit SDMs, which is often biased toward known areas of occurrence or easy access. Further, we did not have an independent dataset for model evaluation. We suggest that a future scrub-bird monitoring project could first involve a 'setting up' phase, where sites are selected using the SDM (e.g., biased to high suitability sites for finding scrub-birds, but also including medium and lower suitability areas with the intention of finding new populations). Sites could then be visited for ground-truthing and a consistent approach to habitat assessment. This site selection could involve as many regions as is feasible based on resourcing and should yield ideally >100 sites per region to provide redundancy in case of accessibility (e.g. floods hindering access). Survey methods (including habitat surveys) should be consistent across the entire area. Based on the detection probabilities recorded in our pilot study, a minimum of three five-minute surveys (with call broadcast) are needed to be confident of rufous scrub-bird occupancy at a given site. Given that scrub-birds (i) are sometimes very easy to detect at sites (e.g. calling on approach to a site), and (ii) spatial replication means that observers must survey a very large area, we suggest a removal design (Mackenzie & Royle, 2005). In a removal design, sites where the target species is detected during a survey round are 'removed' from successive rounds, meaning that sites may be classified as occupied after just one survey, and not visited again. This will free up survey resources during large-scale surveys so that known hotspots of scrub-bird occupancy can be rapidly surveyed and then removed, allowing observers to focus on new, less well-studied locations identified by the SDM that may support unknown populations.

Setting up new monitoring programs for threatened species can be daunting, leaving managers uncertain about what questions to ask and the methods needed to answer them. Our study provides a pathway through this start-up phase of conservation projects that can be easily tailored to the quirks of a species and the needs of conservation managers. Unfortunately, it is not always possible to answer every question on a monitoring wish list, and indeed for some species, there may simply be no suitable methods available for overcoming knowledge gaps. Nevertheless, our approach provides a simple, generalizable model for developing carefully planned, question-driven monitoring even for challenging species. It also highlights the crucial role pilot studies play in the preliminary stages of planning a program, especially when there is uncertainty about methods. We encourage other conservation practitioners to be clear with what they hope to achieve from monitoring from the outset so that conservation efforts are directed toward activities that have a good chance of successfully yielding useful information. Given the scale and urgency of the global extinction crisis, this approach is likely to become increasingly important.

Authors' contributions

DS conceived the ideas and designed methodology; CMY, GO, DS, AS and FA collected the data; CMY, FA and DS analyzed the data; DS, CMY, FA led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Acknowledgements

Thanks to Reegan Walker, Abbey Henry and Rye Gollan and the Hunter LLS for their support of this project.

Funding information

The project received funding from BirdLife Australia and Hunter Local Land Services through funding from the Australian Government's bushfire recovery package for wildlife and their habitat.

Conflict of interest

SV was employed by BirdLife Australia who partly funded the study.

Data availability statement

Data provided on reasonable request.

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Supporting information

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

Data S1.

Table S1. List of spectral attributes retained as variables for downstream analysis of rufous scrub-bird calls. Attributes were measured using function *specan* in the *warbleR* package. Descriptions derived from *warbleR* website.

Table S2. Results of principal components analysis of spectral attributes for the two chip calls. All PC's with an eigenvalue of greater than 1 were retained for further analysis.

Table S3. Proportion of downward chip calls assigned to each individual (numbers in parentheses indicate the sample size of calls). Each column shows to whom each individuals calls were assigned: the assignments were either correct (green squares) or incorrect. The overall classification success of automated individual assignment ranged from 0 to 82%.

Table S4. Proportion of upward calls assigned to each individual. Each column shows to whom each individuals calls were assigned: the assignments were either correct (green squares) or incorrect. The overall classification success of automated individual assignment ranged from 44 to 92%.

Figure S1. Principal components 1 and 2 demonstrating the difference between the upward (red) and downward (blue) chip calls. Each ellipse represents 50% of the variation, and the lack of overlap between the two call types supports the differentiation of these call types in the analyses. The plot also shows the relationship between the 15 attributes of calls listed in Table 1 relative to one another in two dimensional PC space.

Data S2.

Table S1. Summary statistics for the environmental variables that will be used to model the distribution of the rufous scrub bird. Values represent minimum, maximum and mean for each predictor. Bioclimatic variables were extracted from ANUCLIM version 6.1. Some variables were not included in the model due to correlation.

Figure S1. Response curves for the three most important variables per method, ranked in order of importance. *Y* axes represent the suitability of rufous scrub bird habitat and x axis the explanatory variable value. Bioclimatic variables 5 (Max temperature of warmest period) and 9 (Mean Temperature of Driest Quarter) are in degrees °C. Bioclimatic variable 12 (annual rainfall) in millimeters (mm) and forest cover in proportion. The method used for each model is reported on the *Y* axis.

Figure S2. Predicted habitat suitability for presence (1) and background (0) points for rufous scrub-bird.

Table S2. Variable importance for each modelling method, ranked by correlation.

Table S3. Model performance using test dataset (generated using partitioning).

Table S4. Occupancy models ranked by AIC. Preferred model indicated by *.