Articles

Developing Rigorous Monitoring Programs: Power and Sample Size Evaluations of a Robust Method for Monitoring Bird Assemblages

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Abstract

Wildlife population monitoring programs are useful for identifying ecological impacts such as those from local management actions and broader scale influences such as climate change. Increasing the number of species monitored improves robustness of the program towards meeting monitoring objectives. In addition, monitoring at multiple spatial scales should increase the sensitivity of the monitoring program. We developed a monitoring program using unbiased estimates of occupancy at both local and regional scales, and unbiased estimates of density for multiple species of birds with a single protocol. We used transects for sampling ~1,000-ha pastures that consisted of twelve 200-m radius sampling points. We conducted 10-min point counts and recorded distance to each observation using two independent observers, and resampled each of 30 transects over two study sites in South Texas, for a total of four visits in each of 2015 and 2016. We estimated occupancy at two scales using the multiscale model in Program MARK and estimated density using the Distance package in R. We predicted that it would be possible to detect a 50% decline over 25 y with a power of 0.90 in regional occupancy, local occupancy, and density for 36, 37, and 30 species, respectively, on our larger study site, and for 29, 33, and 12 species, respectively, on our smaller study site using two independent observers and four visits. Our work shows it is possible to monitor numerous species within a complex bird assemblage with a simple field protocol. For those interested in implementing a long-term monitoring program that is sensitive to a wide range of potential stressors at local and regional scales, we suggest considering multiscale occupancy and density monitoring for multiple species of birds.

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Introduction

Properly designed wildlife monitoring programs involving state variables such as abundance, density, and occupancy are useful for identifying impacts such as those from local and regional management actions as well as broader scale influences such as climate change. Monitoring data also enhance our ability to develop appropriate plans for sustainable management. Selecting species to monitor requires clearly defined objectives (Yoccoz et al. 2001). Often, one species is used as a surrogate to detect changes in another species or system that are themselves difficult to observe (Caro and O'Doherty 1999). However, the selection of an appropriate surrogate is not straightforward and the effectiveness of surrogates for meeting monitoring objectives may be limited (Simberloff 1998; Andelman and Fagan 2000; Lindenmayer et al. 2002).

The use of multiple species for detecting changes in the larger system of interest is more robust than monitoring a single species (Manley et al. 2004; Gregory et al. 2005). In addition, management actions are just as likely to impact nontarget species as they are to impact target species, with impacts to nontarget species potentially being negative; thus, monitoring multiple species is advisable to detect broader implications of management (Landres et al. 1988; Morrison et al. 1992). However, it is reasonable to expect that as the number and diversity of species included in the monitoring program increase, so too will the resources required. Birds represent an exception because a large number of species inhabiting the same area, but representing a wide range of life histories, can be monitored with a single protocol. Data can be collected for species with a wide range of diets and nesting strategies, and for both residents and migrants, by using simple timed point counts (Hutto et al. 1986).

Point counts alone produce data that are used as indices to populations, which require certain assumptions (e.g., all individuals are equally detectable through space and time). These assumptions are often likely violated, biasing the index, which can substantially compromise our ability to detect change through time (Burnham 1981; Nichols et al. 2000). In addition to a greater likelihood for bias, indices lack measures of uncertainty and thus do not generally provide an opportunity to evaluate statistical power (Anderson 2001; Rosenstock et al. 2002). A well-designed monitoring program requires techniques that account for detection bias and ensure that adequate effort is used such that anticipated analyses will be sensitive enough to detect a predetermined change in the state variable, which can be calculated with a power analysis (Williams et al. 2002; Legg and Nagy 2006). Without such information, long-term monitoring efforts could result in data with high variance and no ability to observe trends.

By conducting multiple observations at individual sampling sites (through time or with multiple observers), point count data can be used to estimate detection probabilities for generating unbiased estimates of occupancy and associated uncertainty (MacKenzie et al. 2006). Estimates of uncertainty can then be used to evaluate the power and sensitivity of the proposed monitoring program. Likewise, recording distances of observed birds from the surveyor allows for estimating detection probability functions that can then be used to generate unbiased estimates of density and associated uncertainty (Buckland et al. 1993, 2001; Rosenstock et al. 2002). Similar to occupancy modeling, the estimates of uncertainty associated with distance sampling can be used to evaluate the power and sensitivity for monitoring changes in population densities.

Measures of abundance or density are often considered the ideal state variable for population monitoring (Williams et al. 2002). However, estimates of occupancy have the potential to provide additional information regarding spatial distribution, habitat relationships, extinction risk, and metapopulation dynamics, and they can generally be done effectively with less effort than is required for abundance or density estimation (MacKenzie et al. 2005, 2006). In addition, occupancy can be used as a surrogate to monitoring density when sampling appropriately sized spatial units (Holt et al. 2002; Efford and Dawdon 2012). The appropriate sampling scale is thus determined by the anticipated application of occupancy-related metrics (i.e., the state variable). Furthermore, different state variables may dictate extremely disparate sampling scales; for example, detecting changes in local population density (e.g., individual grazing pastures) requires sampling with a much finer grain than detecting changes in proportion of management units (e.g., pastures across a ranch) occupied by the species. Pavlacky et al. (2012) presented a hierarchical occupancy model that produced estimates at both a regional and a local scale. Use of a multiscale sampling design and modeling approach for estimating occupancy allows the potential for monitoring two state variables from different spatial scales. Collecting additional measurements of distance for each observation

allows for the potential to monitor density as a third state variable with the same dataset.

Others have considered estimating both state variables of occupancy and density with the same dataset for monitoring a single species (Pederson et al. 2012; Ferreguetti et al. 2017). To our knowledge, the use of both occupancy and density estimates has not been considered for a multispecies monitoring program. Our objectives were to evaluate the level of power achieved through multiple levels of sampling effort for monitoring site occupancy at a local and a regional scale as well as for monitoring density for numerous species of birds from a single source of data. Our overall goal was to provide recommendations to landowners and biologists wanting to develop a rigorous monitoring program for birds.

Methods

Study area

We collected data on the 60,752-ha San Antonio Viejo (SAV; Jim Hogg and Starr counties, Texas, USA) and 10,984-ha El Sauz (ELS; Willacy and Kenedy counties, Texas, USA) ranches that were owned by the East Foundation and managed with the mission of supporting wildlife conservation, private land stewardship, and other public benefits associated with cattle ranching. The SAV was a matrix of woodland (73%), shrubland (18%), grassland (5%), and early-seral vegetation (4%), with approximately half of the ranch in the Coastal Sand Plain Ecoregion and half in Texas-Tamaulipan Thornscrub (Diamond and Fulbright 1990; Fulbright et al. 1990; McLendon et al. 2013b, unpublished report). This region had an average annual precipitation of 57 cm with mean daily high temperature of 29°C (National Oceanic and Atmospheric Administration [NOAA] 2016). The ELS was located 115 km to the east of SAV and adjacent to the Laguna Madre along the Texas Gulf Coast. El Sauz was 36% woodland, 30% wetland vegetation, and 26% grassland (McLendon et al. 2013a). Sixty percent of ELS was in the Coastal Sand Plain ecoregion, with the remaining 40% split evenly between the Laguna Madre Barrier Islands and Coastal Marshes ecoregion and the Lower Rio Grande Valley ecoregion (Diamond and Fulbright 1990; Fulbright et al. 1990; Forman et al. 2009). Annual precipitation for this region was 66 cm, with mean daily high temperature of 26.5°C (NOAA 2016).

Data collection

Transect development. We collected data using the point count method (Hutto et al. 1986) at a series of points along walking transects that were generally square or rectangular. We used a duration of 10 min for each sample and designated 12 survey points per transect such that each transect could be surveyed in its entirety in a single day between 0.5 h before sunrise and ~1200 hours. We spaced observation points a minimum of 400 m apart to minimize the likelihood of sampling the same individuals from multiple locations. We designed the transects in a circuit such that the last point was 400 m from the first point, and we attempted to use a square design (1,600 × 1,600 m) or rectangle (1,200 × 2,000 m) for each transect to balance coverage of our study area with independence among points (Figure 1). We located transects a minimum of 400 m from the edge of individual pastures or ranch boundaries, which we assumed was sufficient to restrict observations to pastures or ranches under survey. We established 30 transects and determined the allocation between the study areas according to ranch size. This resulted in 25 transects on SAV and 5 on ELS. We located one transect in each of 10 pastures along the northern portion of SAV and located the remaining transects randomly across the remaining areas (Figure 1).

Surveys. We began sampling in the third week of April and resampled each transect every 2 wk for a total of four visits each year, ending in the last week of June in both 2015 and 2016. We used a form of double sampling for our surveys where two observers collected data simultaneously, but independent of each other. Upon reaching each point, each observer waited 2 min before conducting the surveys to allow birds to settle after initial disturbance from entering the observation point (Rosenstock et al. 2002). At each point, both observers independently recorded all birds observed by sight or sound (Hutto et al. 1986) within 200 m and used a rangefinder to estimate distance for each detection. Birds that did not land during a survey (flyovers) were not assigned a distance; we did not use these data for our analyses. Observers recorded all individuals seen, including those also heard as visual observations; all others were recorded as aural observations. Once observers completed the survey at a point, they immediately walked to the next point, with the aid of a hand-held global positioning system unit, and repeated the process until all 12 points had been surveyed.

Statistical analysis

Occupancy estimation. We used our data to generate estimates of occupancy and associated variance using the multiscale model in Program MARK (White and Burnham 1999; Nichols et al. 2008). Occupancy is defined as the proportion of sites occupied by a particular species regardless of its abundance (MacKenzie et al. 2006). The multiscale model produces estimates of occupancy at a regional (large) scale (Ψ) as well as at a local (small) scale (θ; Pavlacky et al. 2012). The estimate for Ψ can be interpreted as the proportion of transects that are occupied (a transect is occupied if at least one survey point within the transect is occupied), where θ can be interpreted as the proportion of survey points within a transect that are occupied, given that the transect is occupied. At the scale that we collected data, Ψ is a valuable metric for detecting changes in species' distributions relative to management units (e.g., the proportion of ~1,000-ha pastures that are occupied by
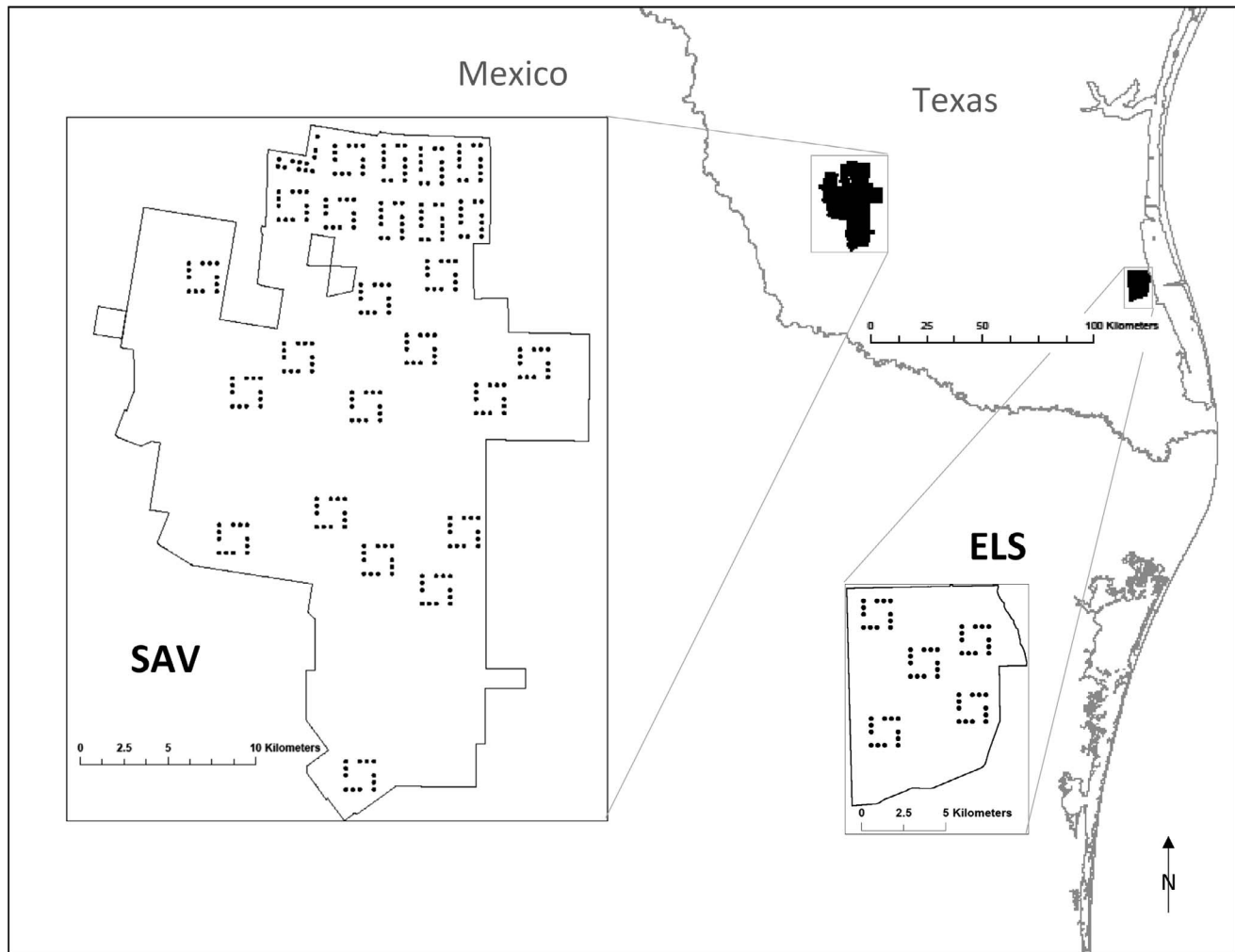
Figure 1. Location of point count transects and configuration of survey locations (dots) within each transect where we surveyed birds on the San Antonio Viejo (SAV) and El Sauz (ELS) study sites in South Texas, USA, in 2015 and 2016.

the species). The θ parameter is potentially influenced by species territory size, local population density, and habitat heterogeneity (Pavlacky et al. 2012). At our scale of data collection, θ is useful for detecting changes in species density within transects that are occupied (e.g., proportion of 200-m radius circles that are occupied by the species within occupied pastures).

We used the detection histories from individual points within a transect as our primary samples, and data from two observers and repeat visits to a point as our secondary samples. We assumed occupancy on both spatial scales would vary between the two sites and years, so we only considered models with terms for ranch and year in both Ψ and θ. The probability that an observer detected a species at a particular point during a particular survey (*p*) partially depends on the activity of individual birds present. It is well established that birds of many species change behavior such as singing rate through the day (Robbins 1981) as well as through the breeding season (Slagsvold 1977). Thus, we also considered models that included terms that allowed *p* to vary

through the season or through time within a day. We included a term that allowed *p* to vary linearly with the order we conducted our surveys as a proxy for time of day. We also considered models that included a quadratic term for survey order to model a nonlinear relationship between *p* and time of day. To model seasonal variation, we considered models with a term that allowed *p* to vary with the order of sampling occasions. In addition, we considered models with a quadratic term for occasion to model a nonlinear relationship between *p* and season as well as additive models with linear terms for both order of survey and occasion. In addition to these six models, we included a model with no terms to ensure we were not overfitting models to the data (Table 1). We used Akaike's Information Criterion adjusted for small sample sizes (AIC$_c$) to compare model fit and used the estimates from the most parsimonious model for our power analyses (Burnham and Anderson 2002; Arnold 2010).

In addition to considering the complete set of data, we generated estimates using all four occasions with data

Table 1. Set of candidate models we fit to individual species' datasets collected from El Sauz and San Antonio Viejo Ranches, South Texas in 2015 and 2016 to estimate regional occupancy (Ψ), local occupancy (θ), and the probability of detection (p) and their corresponding number of parameters (k). A (.) indicates we did not include covariates for the parameter. We included model {Ψ (.), θ (.), p(.)} in each candidate set to ensure we were not overfitting models to the data.

Model	k
Ψ (Year + Ranch), θ (Year + Ranch), p (Time + Date)	9
Ψ (Year + Ranch), θ (Year + Ranch), p (Time^2)	9
Ψ (Year + Ranch), θ (Year + Ranch), p (Time)	8
Ψ (Year + Ranch), θ (Year + Ranch), p (Date^2)	9
Ψ (Year + Ranch), θ (Year + Ranch), p (Date)	8
Ψ (Year + Ranch), θ (Year + Ranch), p (.)	7
Ψ (.), θ (.), p(.)	3

from a single observer randomly selected from both observers to simulate occupancy estimates that would result from approximately half of the field effort. From our list of observations, we attempted to estimate occupancy for a species for a given year if we recorded a minimum of 60 total observations across both study sites with the given effort, with at least 15 observations per study site. If we made 60 observations of a species in a given year, with only 10 observations from one of the study sites, we excluded parameter estimates based on these data from our power analysis. We selected these conservative threshold values to coarsely remove datasets that we expected to be insufficient for providing parameter estimates based on our experience.

Density estimation. We estimated density of individual species using the distance sampling framework (Buckland et al. 2001, 2015) with the Distance package (Miller et al. 2019) in R (R Core Team 2017). This method uses the records of detections for a particular species, along with estimates of the distance of each observation to fit a detection function to each species that estimates the relationship between probability of detection and distance from the observer (Buckland et al. 2001). This information is then used to correct the counts for individuals missed, providing an unbiased estimate of density. By including multiple observations from individual points, additional data are used to improve precision of the density estimates without violating model assumptions (Rosenstock et al. 2002).

We used the same observations from the occupancy estimation, coupled with the estimated distance for each observation, to generate estimates of density of individual species independently for each year of the study. Birds that are observed at great distances where the probability of detection is low can make estimating the detection function difficult and are of little value for estimating density (Buckland et al. 2001). Based on a preliminary analysis of our data, we assumed detection probability beyond 165 m for any species was <10%; thus, we used an initial truncation distance of 165 m for all datasets, excluding all observations recorded beyond this distance from our density estimation. We assumed

the densities of a particular species would differ between ranches; we used multiple-covariate distance sampling with ranch as the covariate and fit two models to the truncated data (Buckland et al. 2015). The two models were a half-normal key function and a hazard rate key function. The multiple-covariate distance sampling procedure pools information between the strata used as covariates to define the shape of the detection function; yet, it allows variation in the detection probability among strata via a scale parameter (Marques et al. 2007). Rosenstock et al. (2002) provide guidelines of 60–100 observations for generating density estimates with a coefficient of variation of 0.15 and Buckland et al. (2001) recommend minimum sample sizes for point counts of 75–100 observations. Thus, we limited our analysis of distance sampling to species for which we had a minimum of 100 observations across both study sites in a given year. If fewer than 15 of these observations were made at a single ranch, we removed them from our dataset and attempted to estimate density for the other study site with the remaining data using conventional distance sampling without the site covariate (Buckland et al. 2015).

We identified the best model for each dataset for a single species in a single year based on AIC$_c$ values. We created a histogram of the observed data with breakpoints that reduced bias from binning by combining commonly rounded distances with the range of distances these observations likely occurred; we used the following breakpoints: 0, 22.5, 37.5, 62.5, 72.5, 87.5, 112.5, 122.5, 135, and 165 m. We instructed our observers to record exact distances when possible, rather than assigning observations to distance bins. However, binning still occurs when specific distances are assigned to observations more frequently than others (e.g., 50 m) and is inevitable when observations are commonly based on calls where the location of the individual animal cannot be visually confirmed, as is typical of most bird surveys (Buckland et al. 2015). We then overlaid the line of the predicted density function from the top-supported model over the histogram of observations in our bins and visually identified the distance bin at which the detection probability dropped below 10–15% (Buckland et al. 2001). We used the lower limit of this distance bin as the new truncation distance for individual datasets and refit the best model as before to generate a final estimate of density and associated standard error (SE) for use in our power analysis. Again, we repeated the previous steps for both years of data using observations from all four occasions with only the observations from a single observer per visit to generate estimates that would result from approximately half of the field effort.

Power analysis

We used two different levels of sensitivity that define an effect size and time frame as a basis for evaluating the power to detect changes in occupancy and density. The

Table 2. Number of species for which our sample sizes met our criteria for estimating the state variables of regional occupancy (Ψ), local occupancy (θ), and density (D), and number of species on each study site for which we predict a 50% decline in 25 y and a 30% decline in 10 y could be detected with a power of 0.90 for each state variable with four or all eight occasions. We collected data at 60 points over five transects at the El Sauz (ELS) site and 300 points over 25 transects at the San Antonio Viejo (SAV) site in South Texas, USA, in 2015 and 2016.

	ELS						SAV					
	Four occasions			Eight occasions			Four occasions			Eight occasions		
No. of species	Ψ	θ	D	Ψ	θ	D	Ψ	θ	D	Ψ	θ	D
Met minimum criteria[a]	27	27	25	34	34	31	33	33	30	42	42	34
Achieved power = 0.9												
50% decline in 25 y	17	19	9	29	33	12	29	28	26	36	37	30
30% decline in 10 y	12	5	0	18	11	0	26	18	9	27	24	10

[a] Criteria for estimating Ψ and θ included a minimum of 60 observations from both sites with $\geq$15 observations from the site of interest in a single year. Criteria for estimating D were similar but required a minimum of 100 total observations.

least sensitive level we considered involved detecting a 50% decline over 25 y, which has been adopted as a standard for the Partners in Flight program to identify most vulnerable species (Rich et al. 2004) and the North American Breeding Bird Survey to detect trends (Sauer 1993). The International Union for Conservation of Nature uses the criterion of a 30% decline over 10 y to define a population as vulnerable (International Union for Conservation of Nature and Natural Resources/ Species Survival Commission Red List Programme 2001); we used this as our second level of sensitivity.

We estimated the power to detect trends in occupancy and density based on our two levels of sensitivity using the power.trend function in the emon package (Barry and Maxwell 2017) in R (R Core Team 2017). We began by simulating linear, declining trends for both sensitivity targets with the estimates of occupancy or density from the corresponding top supported models as the starting points and the model estimated SE as the standard deviation (Gibbs 2000). We then fit a regression line to the projected estimates to test for evidence of a trend using $\alpha = 0.05$. We repeated these steps for a total of 10,000 simulations and calculated power as the proportion of the simulations for which a trend was detected with a p less than α. We estimated power for monitoring Ψ, θ, and density at each site with our two levels of sensitivity separately for 2015 and 2016 and repeated these steps with data simulating a 50% reduction in field effort for each species' dataset that met our minimum threshold for generating estimates.

Results

Observations

We conducted 2,880 point counts (2,400 on SAV and 480 on ELS) in each of 2015 and 2016, resulting in 76,857 observations of 115 species, excluding unconfirmed species and raptors. We considered a species confirmed if we had at least two observations over both years of our study. We excluded raptors because the majority of observations for these species were flyovers and thus not appropriate for our analyses. We had a total of 46 species with a minimum of 60 total observations from both

study sites and a minimum of 15 observations for a single ranch in a single year with our complete set of data (Data S1, *Supplemental Material*). We attempted to estimate occupancy for 34 species and density for 31 species on the ELS site by using detections from both observers (eight occasions; Table 2). With these data, we also attempted to estimate occupancy for 42 species and density for 34 species on the SAV site (Table 2). When we considered data from a single observer (four occasions), we were left with 27 and 25 species that met our criteria for estimating occupancy and density, respectively, on ELS and 33 and 30 species for estimating occupancy and density, respectively, on SAV (Table 2).

State variable estimates

Occupancy. Our Ψ estimates ranged from 1.0, for approximately one-third of all species' datasets that we analyzed, to a low of 0.21 (SE = 0.08) for wild turkey *Meleagris gallopavo* on SAV based on 26 observations (69 total observations) recorded in 2015 with eight occasions (Table S1, *Supplemental Material*). Our lowest estimates of θ was 0.01 (SE = 0.01) for red-winged blackbird *Agelaius phoeniceus* on SAV based on 15 observations from SAV and 137 total observations from four occasions in 2015 (Table S2, *Supplemental Material*). We had two instances where $\theta = 1$; mourning dove *Zenaida macroura* on ELS based on 274 observations (1,469 total observations) from four occasions (Table S3, *Supplemental Material*), and western meadowlark *Sturnella neglecta* on ELS based on 101 observations (106 total observations) from eight occasions (Table S4, *Supplemental Material*).

Density. Our lowest density estimate was for Cassin's sparrow *Peucaea cassinii* on ELS (0.8 individuals per km^2, SE = 0.31), and was based on an average of 1,301.5 observations per y for both sites and 19 site specific observations within a truncation distance of 135 m by using data from eight occasions (Table S4, *Supplemental Material*). Our highest density estimate was for northern mockingbird *Mimus polyglottos* on SAV (87 individuals per km^2, SE = 2.8) based on nearly 4,000 site-specific observations from eight occasions within an average

truncation distance of 117.5 m between our two study sites (Table S1, *Supplemental Material*).

Power

Use of data from a single observer resulted in sufficient data to detect a 50% decline over 25 y in Ψ for 17 species, in θ for 19 species, and in density for nine species on ELS with a power of 0.90 (Tables 2 and 3). Our results suggested this same level of effort should allow for the same sensitivity to detect this decline in Ψ for 29 species, in θ for 28 species, and in density for 26 species on SAV. We predicted that doubling the field effort to include a second observer would allow for the detection of a 50% decline over 25 y in Ψ for 29 species, in θ for 33 species, and density for 12 species on ELS, and in Ψ for 36 species, in θ for 37 species, and density for 30 species on SAV with a power of 0.90. Increasing our sensitivity to the ability to detect a 30% decline over 10 y results in an approximate 25% decline in species we predicted this would be achieved for monitoring Ψ, a 50% decline in species for monitoring θ, and a 75% reduction in species for monitoring density (Tables 2 and 3). We predicted that 10 species could be monitored with eight occasions and 9 species with four occasions for density on SAV at this higher sensitivity, but no species could be monitored for density with an expected power of 0.90 at this higher sensitivity on ELS with either level of effort.

Discussion

Our results showed that by using a multiscale monitoring design that incorporates multiple point counts at each sampling location, the state variable of occupancy at two spatial scales can be used to monitor potentially a large number of species with diverse life histories (Tables S1–S4, *Supplemental Material*). In addition, we showed that by recording distance estimates for each observation, density may also be estimated, providing data for an additional state variable that can also be used for monitoring populations for many of these species with a single field protocol. We believe the additional ability to detect changes in density over time will improve the sensitivity to impacts of a monitoring program that otherwise focuses on occupancy, thus justifying the minor additional effort required.

Precision of occupancy estimates depend on the detection probability in that higher detection probabilities necessarily result in larger numbers of observations for a given occupancy rate. Similarly, species with higher true occupancy will also result in a greater number of observations than for species with low occupancy, given a similar detection probability. Much work has been done to examine the trade-offs between the number of locations sampled and the number of visits to each location for the range of potential detection probabilities and occupancy rates relative to the precision of resulting occupancy estimates (Field et al. 2005; MacKenzie et al. 2006; Bailey et al. 2007). However, these design considerations can only be optimized for a single species or groups of species with similar occupancy and detection probabilities, and to our knowledge, no similar analysis of trade-offs has been conducted for the multiscale framework we used. Nevertheless, our effort and study design were sufficient for estimating occupancy at both spatial scales with high enough precision to monitor a large number of diverse species of birds.

Our use of the multiscale occupancy model likely required a larger sample size and certainly a more complex sampling design and analysis than a simple, single-scale model. We argue the information gained is worth the additional effort and complexity. Management activities can take place at local and regional scales, where climate change occurs at broad spatial extents. Estimating occupancy at two spatial scales allows for the opportunity to link population responses to changing conditions at both local and regional scales that would not be possible with a simple occupancy model (Pavlacky et al. 2012). For example, using occupancy modeling to detect changes in species' distributions that would be expected from climate change requires sampling at a regional scale; yet, we would not expect this scale of sampling to be sensitive to changes in the local density of a species that may result from some management action.

It is important to point out that interpretation of local occupancy depends on the spatial and temporal scale of sampling relative to the typical home range size, movement patterns, and phenology of each species. In our example, we would expect θ to have good sensitivity for detecting changes in local density for many passerines in our study; however, this would not be an appropriate interpretation for species with relatively large movement patterns such as wild turkeys. For such species, changes in θ may be indicative of changes in movement patterns and should be interpreted accordingly.

Estimating density with distance sampling requires greater effort than estimating occupancy to reach a similar level of precision (MacKenzie et al. 2002), which explains why we predicted we would be able to reach our sensitivity targets for more species monitoring occupancy at either scale than density. Buckland et al. (2001) recommended a minimum of 10–20 sampling points should be used for distance sampling, but they warned that more will be necessary to generate a reliable estimate of the encounter rate variance if individuals are patchily distributed. Thus, our use of 60 and 300 sampling points at ELS and SAV, respectively, was likely sufficient. In addition, the number of observations to achieve precise estimates of density from point counts is suggested to be at least 60–100 by Rosenstock et al. (2002) and at least 75–100 by Buckland et al. (2001). These recommendations are greater than those from surveys using transects because distances farther from the observer effectively survey larger areas with point-based surveys than with transects; observations farther from the observer are associated with lower detection probabilities and thus are less useful for fitting the detection function (Buckland et al. 1993). Our estimates of density for many datasets used a truncation distance of <100 m, which excluded all observations made from greater distances from our analysis, reducing the

Table 3. Species which we predict we could detect a 50% decline in 25 y (*) or a 30% decline in 10 y (**) in regional occupancy (Ψ), local occupancy (θ), or density (D) with power = 0.90 on the El Sauz site (ELS) or the San Antonio Viejo site (SAV) in South Texas, USA, by using four occasions or all eight occasions from data collected in 2015 and 2016.

Common name	Species	Four occasions ELS Ψ	θ	D	SAV Ψ	θ	D	Eight occasions ELS Ψ	θ	D	SAV Ψ	θ	D
Ash-throated flycatcher	*Myiarchus cinerascens*				**	*	*	**	*		**	**	*
Audubon's oriole	*Icterus graduacauda*										*	*	
Barn swallow	*Hirundo rustica*	*	*					*	*				
Brown-crested flycatcher	*Myiarchus tyrannulus*		*		*	*	*	**	*		**	*	*
Black-crested titmouse	*Baeolophus atricristatus*		*		**	**	*		*		**	**	*
Bewick's wren	*Thryomanes bewickii*		*		**	**	**	**	*		**	**	**
Brown-headed cowbird	*Molothrus ater*	**	*		**	**	*	**	**	*	**	**	*
Black-throated sparrow	*Amphispiza bilineata*				**	**	*				**	**	**
Bullock's oriole	*Icterus bullockii*										*	*	*
Cactus wren	*Campylorhynchus brunneicapillus*				**	*	*				**	**	
Cassin's sparrow	*Peucaea cassinii*				**	**	**	*	*		**	**	**
Curve-billed thrasher	*Toxostoma curvirostre*				**	*	*				**	**	
Clay-colored sparrow	*Spizella pallida*										*	*	
Chihuahuan raven	*Corvus cryptoleucus*				**	*					**	*	*
Common ground-dove	*Columbina passerina*				**	**	*				**	**	*
Couch's kingbird	*Tyrannus couchii*	**	*		**			**	*		**	*	
Common nighthawk	*Chordeiles minor*								*				
Dickcissel	*Spiza americana*			*			*	*	*	*			*
Eastern meadowlark	*Sturnella magna*		**	*					**	*		*	
Golden-fronted woodpecker	*Melanerpes aurifrons*	**			**	**	**	**	*		**	**	**
Green jay	*Cyanocorax yncas*	**	*		**	*	*	*	*		**	*	*
Greater roadrunner	*Geococcyx californianus*	*			**	**	*	*	*		**	**	*
Great-tailed grackle	*Quiscalus mexicanus*							*	*				
Hooded oriole	*Icterus cucullatus*								*		*		
Laughing gull	*Leucophaeus atricilla*	**	*	*				**	**	*			
Lark sparrow	*Chondestes grammacus*	**			**	*	*	**	*		**	**	*
Long-billed thrasher	*Toxostoma longirostre*							**	*				
Ladder-backed woodpecker	*Picoides scalaris*	*			**	*		*	*		**	**	*
Lesser nighthawk	*Chordeiles acutipennis*										*	*	
Mourning dove	*Zenaida macroura*	**	**	*	**	**	**	**	**	*	**	**	**
Northern bobwhite	*Colinus virginianus*	**	**	*	**	**	**	**	**	*	**	**	**
Northern cardinal	*Cardinalis cardinalis*	**	*	*	**	**	**	**	**	*	**	**	**
Northern mockingbird	*Mimus polyglottos*	**	**	*	**	**	**	**	**	*	**	**	**
Olive sparrow	*Arremonops rufivirgatus*	**	*	*	*	**	*	**	**	*	*	**	*
Painted bunting	*Passerina ciris*	*	*		**	**	**	*	*		**	**	**
Pyrrhuloxia	*Cardinalis sinuatus*				**	**	**	**			**	**	**
Red-winged blackbird	*Agelaius phoeniceus*		*		**			*	*				
Scaled quail	*Callipepla squamata*										*	*	
Scissor-tailed flycatcher	*Tyrannus forficatus*	**	**	*	**	**	*	**	**	*	**	**	*
Vermilion flycatcher	*Pyrocephalus rubinus*										*	*	
Verdin	*Auriparus flaviceps*				**	**	*	*	*		**	**	*
Western meadowlark	*Sturnella neglecta*								**	*			
White-eyed vireo	*Vireo griseus*		*		*	*	*	**	*		**	**	*
Wild turkey	*Meleagris gallopavo*							**	*			*	
White-winged dove	*Zenaida asiatica*					*					*	*	*
Yellow-billed cuckoo	*Coccyzus americanus*	*	*		**	**	*	*	**	*	**	**	*

effective sample size (Tables S1–S4, *Supplemental Material*). Although observations recorded at distances >150 m were not used to estimate density for most species in our dataset, we recommend collecting data out to 200 m. Some species in our datasets, such as eastern meadowlark *Sturnella magna*, consistently had estimated detection probabilities > 0.15 at 150 m with a resulting truncation distance of 165 m. In addition, observations beyond the truncation distance for distance sampling remain useful for estimating occupancy. Finally, observations between 150 and 200 m represented less than 4% of all our observations; collecting these data required minimal additional effort.

Our predicted power for monitoring changes in density was surprisingly low for certain species, despite large sample sizes (>200) within the truncation distance (Tables S1–S4, *Supplemental Material*). This poor precision suggests high, unmodeled variation in the detection function. Marques et al. (2007) suggested including vegetation type characteristics of individual sampling

locations as covariates in multiple-covariate distance sampling to improve precision of estimates, particularly with point-based sampling such as ours. We did not consider covariates other than study site (SAV or ELS) in our initial evaluation of the method to stay focused on our primary study goal; incorporating environmental parameters would have substantially complicated the analyses presented herein given the large number of species on which we collected data. Burnham et al. (2004) showed that distance sampling is robust to pooling data from multiple detection functions. Thus, although our estimates for certain species were imprecise, we do not suspect any unmodeled variation relating to vegetation type resulted in biased estimates of density. We consider our power estimates for monitoring density to be conservative and likely would be improved upon with the inclusion of meaningful site covariates, depending on the goals of a particular study.

Our method of estimating density from both visual and aural observations combined may not be appropriate for all species in our study. It is likely that the true detection function for visual observations differs from that for aural observations. If this is the case, including both and attempting to fit a single detection function to the data will result in reduced precision in density estimates. Because visual observations tend to be made closer to the observer than aural observations, it would not be appropriate to use whether an individual was seen or not as a covariate in multiple-covariate distance sampling (Marques et al. 2007). Furthermore, if only a portion of the population can be assumed to be available for one of the forms of detection (e.g., a species for which only males are expected to sing or call during the breeding season), combining both may result in a biased estimate of density (i.e., the estimate may represent something other than 100% of the statistical population). Buckland et al. (2006) recommend limiting observations to aural detections and possibly only detections of singing males to estimate the male segment of the population; however, this requires additional consideration and assumptions because for some species, unmated males sing more than mated males and singing rate may vary significantly through the breeding season. Our method of data recording precluded us from estimating detection functions separately for each detection type. We recommend others considering using their data to estimate density with distance sampling to record whether each individual was observed visually, aurally, or both, and if aurally, whether by song or other. This will allow estimation of detection probability separately for each detection type such that appropriateness of combining observations can be evaluated. Furthermore, if it is determined that the sources of observations should not be combined, these results can be used, along with assumptions of availability, to determine which observation type(s) should be used for estimating density. Although the methods we used may have resulted in some of our density estimates being biased, we do not believe this bias would impact our estimated power to detect our stated population changes. However, further consider-

ation would be necessary to accurately define the statistical population being monitored.

Our results show that there is no single optimal level of effort for all situations and that the return on increasing effort varies by study area, species, and state variable being monitored. Our doubling of effort by using two observers, increasing our total occasions of data collection for each location from four to eight, improved our estimated power for monitoring occupancy at both scales and for monitoring density. This 100% increase in effort generally resulted in much less than a 100% increase in the number of species that we predicted could be monitored at one of the specific sensitivity levels with a power of 0.90. The greatest increase we saw was for the smaller ELS dataset, where the predicted number of species that could be monitored to detect a 50% decrease over 25 y in Ψ and θ increased by $\sim$70% and in density increased by 33%.

Our work shows it is possible to monitor multiple state variables for numerous species within a complex bird assemblage by using a simple field protocol. The amount of effort necessary to meet the monitoring objectives depends on a number of factors, including the stated level of sensitivity. Our findings illustrated that increasing the sensitivity requirements of a monitoring program reduces the number of species that could be monitored with a specific power and amount of effort. Put another way, increasing the sensitivity requirements will increase the required precision of estimated state variables for any given species and thus increase the minimum amount of data needed.

Management implications

For those interested in implementing a long-term monitoring program that is sensitive to changing conditions at local and regional scales, we suggest considering multiscale occupancy and density monitoring for multiple species of birds such as we have presented herein. The methods we outline may represent a modest increase in the data that managers currently collect; yet, they should result in a monitoring program that is substantially more sensitive to environmental stressors. Our study design involved conducting point counts with a two-scale sampling scheme: sampling over multiple, repeat occasions, with multiple observers, or with both; and collecting distance estimates for each observation. The species for which we found it feasible to monitor in our study should prove sensitive to broad implications of a wide range of potential stressors, given the diverse life histories represented by the group (Table 3). Thus, a study such as ours should have the potential to meet a variety of monitoring objectives.

The amount of required effort to meet a program's objectives will also depend on factors such as population sizes and detection probabilities of species of interest as well as the size and spatial heterogeneity of the monitoring area of interest. For these reasons, it is imperative that managers begin with a pilot study to determine required effort and ensure adequate number

of sampling sites, number of subsampling locations, and number of replicate visits to each sampling location are used. Such planning can greatly reduce the possibility of wasting resources on monitoring programs that fail to meet objectives.

The designs we presented herein were not developed for monitoring a particular focal species; they were designed to maximize the number of species for which significant changes in populations over specific time periods would be detected. Point counts, as we suggest for a long-term monitoring program, are an ideal tool for collecting population state data for a large number of bird species. However, using point counts in the sampling designs we outlined herein may not be an adequate method for monitoring rare species simply because sample sizes necessary for desired sensitivity levels are usually not reached. Should it become desirable to attain greater monitoring sensitivity for focal species (e.g., rare species or game species such as the wild turkey), we would recommend using focused studies such as spot mapping and nest monitoring (Ralph et al. 1993). We suggest that a monitoring program with a broad scope, such as the program we have presented herein, be used to identify populations that are declining or are otherwise rare for which focused studies can then be implemented.

Supplemental Material

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Table S1. Average sample sizes and estimates of regional occupancy (Ψ), local occupancy (θ), and density (N/km^2) for a single year from data collected on the San Antonio Viejo study site in South Texas in 2015 and 2016 by using two observers and four replicate visits. The complete sample size is denoted as N, where N_s indicates the sample size for the specific study site. Trunc is the truncation distance used for estimating the detection function for distance sampling, Nt is the number of observations from both sites made within the truncation distance, and Nts is the number of observations from the specific site made within the truncation distance. Estimated power to detect a 50% decline in 25 y in occupancy or density is indicated by P_{25}; estimated power to detect a 30% decline in 10 y is indicated by P_{10}. Species with an observed 100% occupancy at either scale were assigned a standard error of 0.

Found at DOI: https://doi.org/10.3996/042019-JFWM-027.S1 (67 KB DOCX).

Table S2. Average sample sizes and estimates of regional occupancy (Ψ), local occupancy (θ), and density (N/km^2) for a single year from data collected on the San Antonio Viejo study site in South Texas in 2015 and 2016 by using a single observer and four replicate visits. The complete sample size is denoted as N, where N_s indicates

the sample size for the specific study site. Trunc is the truncation distance used for estimating the detection function for distance sampling, Nt is the number of observations from both sites made within the truncation distance, and Nts is the number of observations from the specific site made within the truncation distance. Estimated power to detect a 50% decline in 25 y in occupancy or density is indicated by P_{25}, estimated power to detect a 30% decline in 10 y is indicated by P_{10}. Species with an observed 100% occupancy at either scale were assigned a standard error of 0.

Found at DOI: https://doi.org/10.3996/042019-JFWM-027.S1 (67 KB DOCX).

Table S3. Average sample sizes and estimates of regional occupancy (Ψ), local occupancy (θ), and density (N/km^2) for a single year from data collected on the El Sauz study site in South Texas in 2015 and 2016 by using a single observer and four replicate visits. The complete sample size is denoted as N, where N_s indicates the sample size for the specific study site. Trunc is the truncation distance used for estimating the detection function for distance sampling, Nt is the number of observations from both sites made within the truncation distance, and Nts is the number of observations from the specific site made within the truncation distance. Estimated power to detect a 50% decline in 25 y in occupancy or density is indicated by P_{25}; estimated power to detect a 30% decline in 10 y is indicated by P_{10}. Species with an observed 100% occupancy at either scale were assigned a standard error of 0.

Found at DOI: https://doi.org/10.3996/042019-JFWM-027.S1 (67 KB DOCX).

Table S4. Average sample sizes and estimates of regional occupancy (Ψ), local occupancy (θ), and density (N/km^2) for a single year from data collected on the El Sauz study site in South Texas in 2015 and 2016 by using two observers and four replicate visits. The complete sample size is denoted as N, where N_s indicates the sample size for the specific study site. Trunc is the truncation distance used for estimating the detection function for distance sampling, Nt is the number of observations from both sites made within the truncation distance, and Nts is the number of observations from the specific site made within the truncation distance. Estimated power to detect a 50% decline in 25 y in occupancy or density is indicated by P_{25}; estimated power to detect a 30% decline in 10 y is indicated by P_{10}. Species with an observed 100% occupancy at either scale were assigned a standard error of 0.

Found at DOI: https://doi.org/10.3996/042019-JFWM-027.S1 (67 KB DOCX).

Data S1. Species observations for point counts conducted on the San Antonio Viejo (SAV) and El Sauz (ELS) study sites in South Texas in 2015 and 2016 by two observers (randomly assigned A or B). Observation distances are in meters, and four-letter species codes are according to the American Ornithological Union's list

of bird species in the North and Middle America Checklist, 7th edition (www.checklist.aou.org).

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