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Monitoring occupancy of bats with acoustic data: power and sample size recommendations

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Monitoring occupancy of bats with acoustic data: power and sample size recommendations

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ABSTRACT.—Bats are difficult to study due to their nocturnal, cryptic, and highly vagile nature. Ongoing advances in acoustic recording hardware and call classification software have made species detection and activity monitoring more feasible. Our objectives were to determine the effort necessary to monitor bat assemblages using an occupancy framework and acoustic data and to provide guidelines for researchers interested in developing similar monitoring programs. We collected data at 2 study areas in South Texas from June through September in 2015, 2016, and 2017. We used Pettersson D500X Mk II real-time full-spectrum detectors and classified sound files using SonoBat bat call analysis software. We attempted to collect data during 2 visits to individual sites, with up to 5 consecutive nights per visit each year. We estimated occupancy rates for each species in each study area using occupancy models in Program MARK and included terms to define trends in detection probability through the season. Over the 3 years of our study, we sampled 106 sites with 803 sampling nights and classified a total of 2880 sound files to 7 species. Data sets for 6 of the species supported models indicating that detection probability varied throughout our sampling period. Our results generally indicate that sample sizes between 10 and 20 sites would be required to detect declines in occupancy of 50% over 25 years using 10 nights per site with a starting occupancy rate of 0.70. Detecting declines of 30% in 10 years may require >75 sampling sites. Finally, our analysis shows that recognizing seasonal variation in detection probability, and then timing surveys accordingly, can greatly reduce sample size requirements.

RESUMEN.—Los murciélagos son difíciles de estudiar debido a su naturaleza nocturna, críptica y altamente vágil. Los avances en las herramientas de grabación acústica y el software de clasificación de llamadas han facilitado la detección de especies y el monitoreo de actividad. Nuestros objetivos fueron (1) determinar el esfuerzo necesario para monitorear los ensamblajes de murciélagos, utilizando un sistema de ocupación y datos acústicos, y (2) proporcionar pautas para los investigadores interesados en desarrollar programas de monitoreo similares. Recopilamos datos en dos áreas de estudio en el sur de Texas desde junio hasta septiembre en 2015, 2016 y 2017. Usamos los detectores de espectro completo en tiempo real Pettersson D500X Mk II y archivos de sonido clasificados usando el software de análisis de llamadas de murciélagos SonoBat. Intentamos recopilar datos durante dos visitas a diferentes sitios de hasta cinco noches consecutivas por visita cada año. Calculamos las tasas de ocupación de cada especie en cada área de estudio utilizando modelos de ocupación del Programa MARK e incluimos términos para definir las tendencias en la probabilidad de detección a lo largo de la temporada. Durante los tres años de nuestro estudio, tomamos muestras durante 803 noches de 106 sitios y clasificamos un total de 2880 archivos de sonido perteneciente a siete especies. La base de datos de seis de las especies respaldó modelos que indican que la probabilidad de detección varió a lo largo de nuestro período de recolección de muestras. Nuestros resultados mayormente indican que se necesitarían muestras de entre 10 y 20 sitios para detectar disminuciones en la ocupación del 50% durante 25 años durante 10 noches por sitio con una tasa de ocupación inicial de 0.70. Mientras que, para detectar disminuciones del 30% en 10 años se podrían requerir más de 75 sitios de muestreo. Por último, nuestro análisis indica que el tener en cuenta que la probabilidad de detección varía según la estación y al sincronizar el muestreo de manera acorde puede reducir en gran medida los requisitos de tamaño de la muestra.

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Bats represent about one-fifth of the world's mammalian species, with both diversity and abundance highest in lower latitudes (Wilson and Reeder 2003). Collectively, this diverse taxon provides a number of critical ecosystem services such as insect predation, seed dispersal, and plant pollination (Patterson et al. 2005, Kunz et al. 2011). Additionally, Kalka et al. (2008) concluded that bat predation on herbivorous insects reduces herbivory in the tropics more than bird insectivory does, and they suggested that the same relationship likely holds in temperate zones as well. These services have potentially large impacts on agriculture and forest and range management.

Of the over 1200 recognized species of bats worldwide, 18% are listed as Threatened by the International Union for Conservation of Nature (IUCN), with an additional 15% having insufficient data to determine their conservation status (Frick et al. 2020). In North America, the recent introduction of the fungus that causes the disease White Nose Syndrome has devastated many bat species in the northeastern United States and is predicted to result in regional extinctions of numerous species' populations (Frick et al. 2010, 2015, Turner et al. 2011). Additionally, bat populations are impacted by climate change, development for wind power, and certain crop and rangeland management practices (Kunz and Pierson 1994, Jones et al. 2009, Frick et al. 2020). Furthermore, removal or control of trees to improve grazing for livestock may limit roosting resources or degrade landscape structure such as edge habitat and cover needed as foraging habitat for some species of bats, thereby reducing or limiting their populations in these areas (Humphrey 1975, Racey and Entwistle 2003, Jones et al. 2009). On the other hand, artificial water sources intended for livestock provide foraging sites and water for bats in areas where these resources are otherwise uncommon (Fulbright et al. 1990, Fern et al. 2018).

As our understanding of recent and potential future changes in regional bat populations grows, the general interest in, and perhaps the necessity of, monitoring these populations will also increase. Historically, bats have been difficult to study, primarily because of their nocturnal, cryptic, and highly vagile nature (O'Shea et al. 2003). Ongoing improvements

in acoustic recording hardware and call classification software have made species detection and activity monitoring more feasible (Parsons and Szewczak 2009, Frick 2013). Furthermore, occupancy studies based on acoustic data can provide information necessary for detecting changes in population metrics such as regional occurrence and activity (Weller 2008, Rodhouse et al. 2012). Our primary objectives were to determine optimal methods and the necessary level of effort to monitor the bat assemblage on the East Foundation ranches in southern Texas using an occupancy framework and acoustic data, with the secondary objective of providing broadly applicable guidelines for determining required effort and sample sizes for others interested in developing similar bat monitoring programs.

STUDY AREA

We collected data on the 60,752-ha San Antonio Viejo (Jim Hogg and Starr counties; hereafter SAV) and 10,984-ha El Sauz (Willacy and Kenedy counties; hereafter ELS) ranches in southern Texas. These ranches are owned by the East Foundation and managed as a working laboratory to support wildlife conservation, private land stewardship, and other public benefits associated with ecologically sound cattle ranching. One-hundred-year annual precipitation averages for the period ending in 2015 ranged from ~54 cm at SAV to ~63 cm at ELS (PRISM Climate Group 2018). Annual rainfall totals for 2015, 2016, and 2017 were 66, 60, and 46 cm, respectively, at SAV and 96, 55, and 56 cm, respectively, at ELS (PRISM Climate Group 2018).

The SAV is a matrix of woodland (73%), shrubland (18%), and grassland (5%), 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). The ELS is located 117 km to the east of SAV and adjacent to the Laguna Madre along the Texas Gulf Coast. El Sauz is made up of 30% wetland vegetation, with the remainder of the ranch a matrix of woodland (36%), grassland, (27%), and shrubland (5%). Sixty percent of ELS is 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

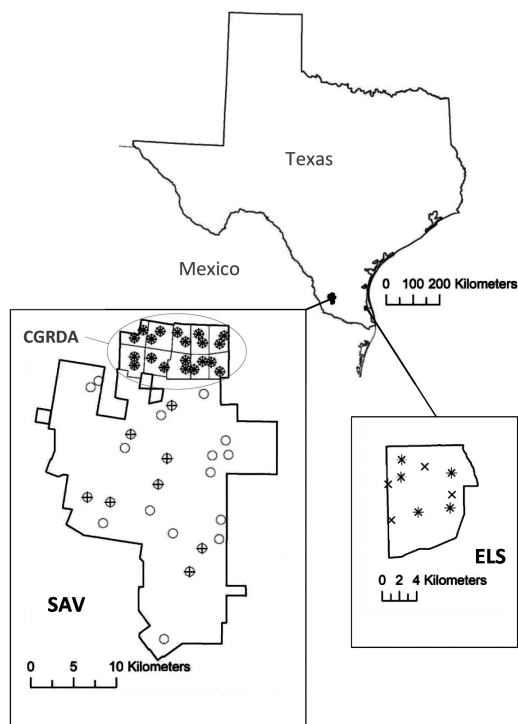


Fig. 1. Sites on East Foundation lands where we recorded bat passes in 2015 (+), 2016 (x), and 2017 (o), including San Antonio Viejo (SAV), the Coloraditas Grazing Research and Demonstration Area pastures (CGRDA) on SAV, and El Sauz (ELS) in southern Texas, USA. Combined symbols represent sites that were surveyed in multiple years.

Valley ecoregion (Diamond and Fulbright 1990, Fulbright et al. 1990, Forman et al. 2009).

METHODS

We randomly located 2 sampling sites in each of 10 pastures associated with a long-term grazing study being conducted in the Coloraditas Grazing Research and Demonstration Area (hereafter CGRDA) on the northern 7300 ha of SAV (Fig. 1). We randomly located all other sampling sites on the remaining southern portions of SAV (SAVs) and on ELS. We spaced all sampling locations a minimum of 400 m from ranch or pasture boundaries and a minimum of 1 km from other sampling locations and assumed that this spacing regime resulted in independent samples representative of the pastures of interest. We were primarily interested in monitoring summer resident bats; thus, we sampled from about June through September in

2015, 2016, and 2017. The number of sites we sampled in a year was determined by the number of detection units we had available (5 in 2015, 4 in 2016, and 6 in 2017). We attempted to survey each site for a minimum of 5 consecutive successful nights before moving the detectors (Gorresen et al. 2008, Skalak et al. 2012). A successful night was defined as a night without rain or high winds and when equipment did not fail. Once all sites were visited, we attempted a second visit to each site for 5 additional successful nights, as time and equipment allowed. Our primary goal was to determine the number of sites and visits needed to monitor the occurrence of most of the bat species through time. Our sampling intensity per site was likely adequate to sample local species richness; however, we recognize that more intensive sampling per site might be needed to identify very rare species (Moreno and Halffter 2000, Skalak et al. 2012, Froidevaux et al. 2014, Green et al. 2020).

We recorded ultrasonic bat calls using Pettersson D500X Mk II real-time full-spectrum detectors (Pettersson Elektronik, Uppsala, Sweden). We used external microphones connected by 7.62-m-long (25-ft-long) microphone cables and extended to approximately 0.5 m above the canopy of the surrounding vegetation using a telescoping extension pole. Wind noise can trigger the detector to record and interfere with the recording of actual bat calls. We directed the microphones approximately 30° above horizontal and in a north-westerly direction to avoid prevailing winds from the southeast. Additionally, we used the cone-shaped horn that came with the microphones for additional protection from wind and rain and increased directionality and sensitivity. We ran detectors from 15 min before sunset to 15 min after sunrise using a relative timer built into the detector. The relative timer function estimated daily times of sunrise and sunset based on geographic location. We adjusted detector input volume (gain) and the requirements for the duration of a bat call to trigger a recording (trigger sensitivity) on a case-by-case basis because wind and other environmental factors could trigger unwanted recordings and deplete detector battery life. We predominantly used a “low” trigger sensitivity setting because lower settings generally discriminate against non-bat recordings. We

set the intensity at which a sound would be recorded (trigger level) to 80 dB because a typical bat calls at ~ 110 dB (Surlykke and Kalko 2008), and we wanted to detect bats that might call more quietly or indirectly to our microphones. We also programmed detectors to pause for 5 s between recordings to discourage the recording of multiple sound files during a single bat pass. Lastly, we used a sampling frequency of 500 kHz and turned off the low-frequency attenuation setting to sample the spectrum of frequency ranges utilized by potential bat species on the ranches.

To organize bat recordings prior to processing, we attributed sound files with metadata that included site, detector, date, and time stamp. We then filtered attributed sound files using the SonoBat 4.2 high-grade batch scrubber. We set the batch scrubber to a “medium” sensitivity to reject poor-quality calls; however, we included calls from 5 to 10 kHz to include potential bat species that vocalize at lower frequencies (e.g., Rafinesque’s big-eared bat [*Corynorhinus rafinesquii*]). This ensured that the clearest bat calls were isolated for species identification and also reduced the number of “noise” files, which generally included insect, wind, or other ambient sound. We processed the filtered sound files, using the most up-to-date SonoBat regional classifier, as follows. In 2015, we classified bat recordings to species using SonoBat 3.0 and a minimum 94% confidence (provided by the classifier) for automated identification. As upgraded software became available in 2016 and 2017, we used SonoBat 4.0 and then SonoBat 4.2 classifiers, respectively. The SonoBat classifiers did not automatically assign a species to recordings that contained more than one bat call or those that fell below a 94% probability of identification confidence. Instead, we manually vetted these recordings to assign a species classification by comparing a sonogram of the recording in question with those of candidate species suggested by the software using a reference library of known species. We then summarized classified recordings by site, sampling night, and species.

We estimated ranch-specific occupancy rates for individual species by using the simple occupancy model in Program MARK (White and Burnham 1999). We defined occupancy as the proportion of sample sites occupied by a

particular species. We used data collected during repeat visits to the same locations to generate estimates of the probability of detection (p), which we then used to correct the record of detections to produce unbiased estimates of occupancy (MacKenzie et al. 2006). This model accounted for missing data such that missing nights resulting from equipment failure did not bias our estimates. We limited our analysis to 5 successful nights from each sampling visit if more than 5 nights were collected, resulting in detection histories of 10 occasions. We assumed the detection probability may have changed as a function of time through the season; thus, we included models in our candidate set with a linear term for ordinal date to allow for a linear change in p through the season, and a quadratic term for ordinal date to allow for curvilinear changes through the season. We included group covariates in all models to produce separate estimates of occupancy for the CGRDA, the rest of SAV (SAVs), and ELS. We compared all 3 models using Akaike’s information criterion adjusted for small sample sizes (AICc; Burnham and Anderson 2002, Arnold 2010) and used the model with the most support for each species’ data set to generate parameter estimates. We analyzed the data from 2015 and 2017 a second time to generate species-specific estimates of occupancy for the entire SAV in order to get estimates and standard error values from a larger sample size.

We identified 2 levels of sensitivity to assess power and determine sample sizes. The first level was to detect a 30% decline in occupancy rate over 10 years and was based on the criteria for designating a species as Vulnerable by the International Union for Conservation of Nature (IUCN 2012). We selected a second level that was less sensitive than the first and defined it as the ability to detect a 50% decline in occupancy over 25 years. We estimated the power to detect trends based on our 2 sensitivity targets (Baumgardt et al. 2019) using the ‘*emon*’ package (Version 1.3.2; Barry and Maxwell 2017) in R (Version 3.3.2; R Core Team 2017). We began by generating linear trends for each of the sensitivity targets, with the occupancy estimate from the top supported model as the starting point with a normal distribution and the estimated SE as the standard deviation. We then fitted a linear regression line to the

TABLE 1. Number of sound files of bat calls recorded by species in each year in each study area. Data were collected in the Coloraditas Grazing Research and Demonstration Area (CGRDA) on the northern portion of San Antonio Viejo, the southern portion of the San Antonio Viejo (SAVs), and El Sauz (ELS), southern Texas, USA, in 2015, 2016, and 2017.

Species	Common name	Number of passes detected						
		2015			2016		2017	
		CGRDA	SAVs	ELS	CGRDA	ELS	CGRDA	SAVs
<i>Lasiurus borealis</i>	Eastern red bat	50	51	565	29	328	45	170
<i>Lasiurus cinereus</i>	Hoary bat	102	5	5	1	0	6	4
<i>Lasiurus intermedius</i>	Northern yellow bat	15	2	1	7	8	0	0
<i>Myotis velifer</i>	Cave myotis	148	14	0	71	2	349	116
<i>Nycticeius humeralis</i>	Evening bat	5	0	76	24	114	85	176
<i>Perimyotis subflavus</i>	Tricolored bat	0	0	6	3	38	5	2
<i>Tadarida brasiliensis</i>	Mexican free-tailed bat	1	0	0	12	5	102	132
Sites sampled		20	8	5	20	10	20	23
Successful nights		119	40	24	151	50	194	225

projected occupancy estimates to test for evidence of a trend ($\alpha = 0.05$). 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 $P < \alpha$. We repeated these steps using estimates from each species in each year for each study area.

To further partition the impacts of occupancy estimates and sample size on power, we used the *glm* function in R to run a multiple logistic regression model using the results from each of the power analyses. The estimated occupancy rate and the number of sites sampled for the estimate were the independent variables, and the estimated power to detect a 50% decline in 25 years was the dependent variable. We ran a second regression model with the estimated power to detect a 30% decline in 10 years as the dependent variable. For each of the regression models, we then used the *predict* function in R to project the resulting power for various occupancy rates and number of sites surveyed.

Finally, we ran additional simulations through our power analysis with a range of occupancy and SE estimates to calculate the coefficient of variation (CV) that was required to reach each of our 2 sensitivity targets with a power of 0.90. We then calculated the number of survey sites that would be required to reach occupancy estimates with these CV values based on our date-specific estimates of detection probabilities for our mean survey days, 10 occasions, and a range of occupancy estimates, using equation 6.3 from MacKenzie et al. (2006):

$$s = \frac{\Psi}{\text{Var}(\hat{\Psi})} \left[(1 - \Psi) + \frac{(1 - p^*)}{p^* - Kp(1 - p)^{k-1}} \right],$$

where s is the number of samples, Ψ is the occupancy rate, p^* is the probability that the species was detected at least once throughout the 10-occasion sampling duration, p is the estimated detection probability for a single occasion, and K is the number of occasions ($K = 10$). For species that had a time-varying p , we used the average of the estimates for the specific time frame. We repeated these steps using the 10 survey days that corresponded with our estimated maximum detection probability during our sampling time frame (p_{\max}) to explore the effects of sample timing on required sample size.

RESULTS

In 2015, we sampled 28 sites on SAV: 20 in the CGRDA pastures and 8 across the remaining southern portion of SAV (SAVs). Additionally, we sampled at 5 locations on ELS. We sampled the same 20 locations in the CGRDA again in 2016 and 2017. In 2016, we increased the number of points sampled on ELS to 10 but did not sample any locations on SAVs. In 2017, we sampled 23 locations on SAVs, but did not sample any locations on ELS (Table 1). We experienced multiple problems with the detectors, memory cards, and weather that resulted in success rates of 80% in 2015, 85% in 2016, and 86% in 2017 for detector nights attempted. Between these success rates and the limitations due to available equipment, we averaged 7.57 (SD = 2.63) successful nights

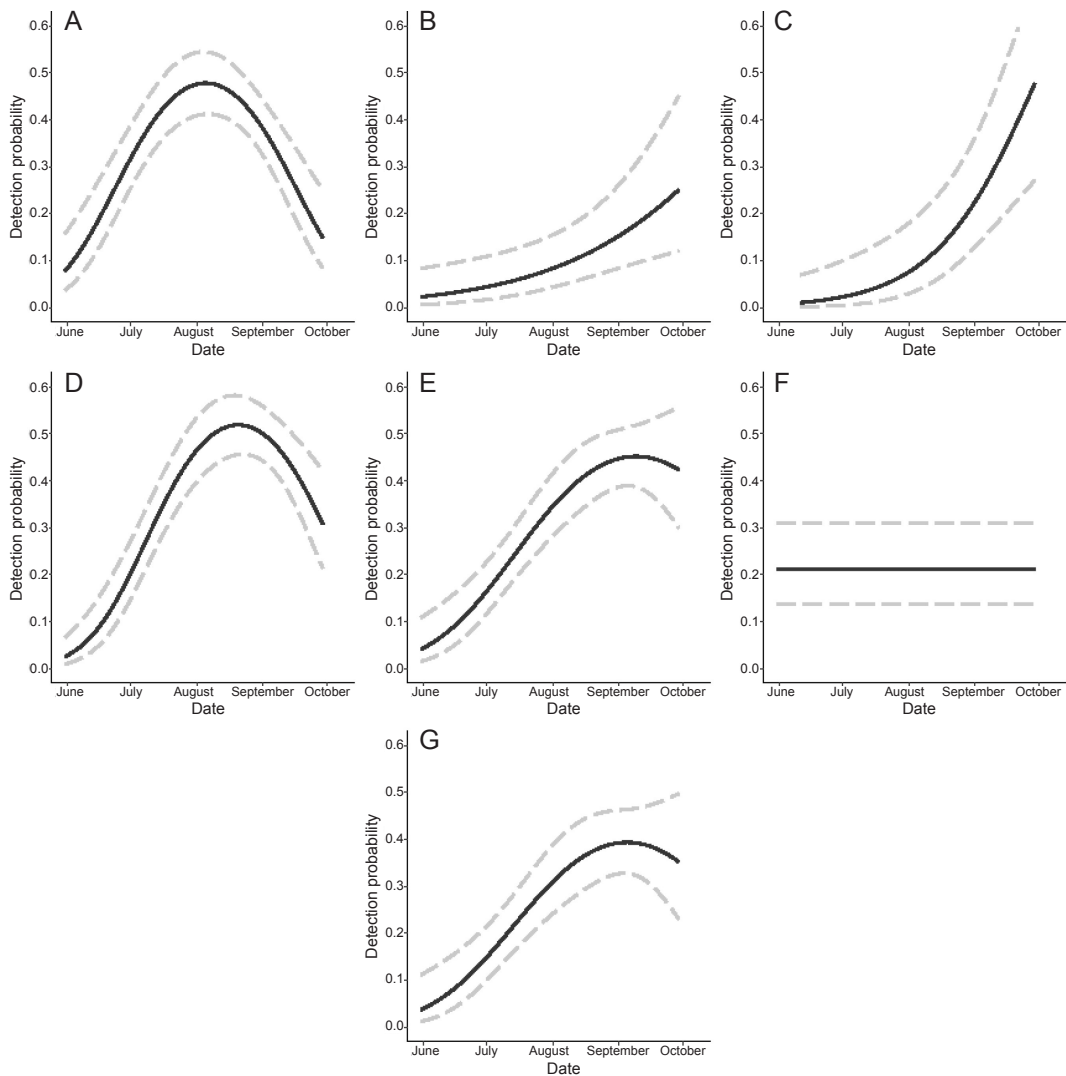


Fig. 2. Detection probability estimates through the sampling season for the 7 species of bats we detected on San Antonio Viejo and El Sauz in southern Texas, USA, during 2015, 2016, and 2017. **A**, Eastern red bat (*Lasiurus borealis*). **B**, Hoary bat (*Lasiurus cinereus*). **C**, Northern yellow bat (*Lasiurus intermedius*). **D**, Cave myotis (*Myotis velifer*). **E**, Evening bat (*Nycticeius humeralis*). **F**, Tricolored bat (*Perimyotis subflavus*). **G**, Mexican free-tailed bat (*Tadarida brasiliensis*). Dashed lines represent 95% confidence bands. We sampled from ordinal date 151 (31 May) to ordinal date 272 (29 September).

per site each year, resulting in a total of 183 successful nights of sampling in 2015, 201 in 2016, and 419 in 2017 (Table 1). We classified a total of 1046, 642, and 1192 sound files in 2015, 2016, and 2017, respectively, to 7 species (Table 1).

The models with the most support for describing occupancy for hoary bat (*Lasiurus cinereus*) and northern yellow bat (*Lasiurus intermedius*) contained a term for ordinal

date in the detection probability, suggesting that p increased linearly through our sampling season (Fig. 2, Appendix 1). However, note that models were fit on the logistic scale and that back-transforming estimates resulted in a slightly nonlinear curve. The best-supported models for describing occupancy for eastern red bat (*Lasiurus borealis*), cave myotis (*Myotis velifer*), evening bat (*Nycticeius humeralis*), and Mexican free-tailed bat

TABLE 2. Estimates of occupancy rates for each species in each year in each study area. Data were collected in the Coloraditas Grazing Research and Demonstration Area pastures on the northern portion of San Antonio Viejo (CGRDA), the southern portion of San Antonio Viejo (SAVs), and El Sauz (ELS) in southern Texas, USA, in 2015, 2016, and 2017. We also combined the CGRDA and SAVs data sets to generate occupancy estimates for all of the San Antonio Viejo (SAV) in 2015 and 2017. Numbers in parentheses are standard error estimates. Occupancy rates without reported SE values were not estimated either because of no observations ($\Psi = 0$) or because the species was detected at most sites or every site ($\Psi = 1$). We did not attempt to estimate occupancy rates for species that had no classified observations from a single site in a single year.

Species	Estimated occupancy rate											
	2015				2016				2017			
	CGRDA	SAVs	SAV	ELS	CGRDA	ELS	CGRDA	ELS	CGRDA	SAVs	SAV	SAVs
Eastern red bat	0.62 (0.13)	0.81 (0.17)	0.68 (0.10)	0.91 (0.21)	0.47 (0.12)	1	0.47 (0.12)	1	0.61 (0.11)	0.75 (0.09)	0.69 (0.07)	0.75 (0.09)
Hoary bat	0.71 (0.27)	0.96 (0.46)	0.77 (0.26)	1	0.08 (0.08)	0	0.08 (0.08)	0	0.23 (0.13)	0.27 (0.13)	0.25 (0.09)	0.27 (0.13)
Northern yellow bat	0.99 (0.46)	0.71 (0.47)	0.89 (0.38)	0.54 (0.48)	0.27 (0.12)	0.64 (0.31)	0.27 (0.12)	0.64 (0.31)	0.96 (0.05)	0.62 (0.10)	0.78 (0.07)	0.62 (0.10)
Cave myotis	0.53 (0.13)	0.41 (0.19)	0.49 (0.11)	0	0.73 (0.11)	0.26 (0.16)	0.73 (0.11)	0.26 (0.16)	0.92 (0.07)	0.82 (0.09)	0.87 (0.06)	0.82 (0.09)
Evening bat	0.12 (0.08)	0	0.09 (0.06)	1	0.47 (0.12)	0.93 (0.14)	0.47 (0.12)	0.93 (0.14)	0.22 (0.10)	0.10 (0.07)	0.15 (0.06)	0.10 (0.07)
Tricolored bat	0	0	0	0.57 (0.31)	0.19 (0.10)	0.88 (0.22)	0.19 (0.10)	0.88 (0.22)	0.73 (0.11)	0.88 (0.08)	0.80 (0.07)	0.88 (0.08)
Mexican free-tailed bat	0.06 (0.06)	0	0.04 (0.04)	0	0.33 (0.11)	0.44 (0.20)	0.33 (0.11)	0.44 (0.20)	20	23	23	23
Sites sampled	20	8	28	5	20	10	20	10	20	23	43	23

TABLE 3. Estimates of power to detect a 50% decline in occupancy over 25 years (first number in each column) and a 30% decline in occupancy over 10 years (second number in each column) for each species we detected in each year in each study area. Data were collected in the Coloraditas Grazing Research and Demonstration Area pastures on the northern portion of San Antonio Viejo (CGRDA), the southern portion of San Antonio Viejo (SAVs), and El Sauz (ELS) in southern Texas, USA, in 2015, 2016, and 2017. We also combined the CGRDA and SAVs data sets to generate occupancy estimates for all of San Antonio Viejo (SAV) in 2015 and 2017.

Species	Estimated power											
	2015				2016				2017			
	CGRDA	SAVs	SAV	ELS	CGRDA	ELS	CGRDA	ELS	CGRDA	SAVs	SAV	SAVs
Eastern red bat	0.94, 0.26	0.94, 0.26	1.00, 0.42	0.89, 0.20	0.83, 0.18	1.00 ^a , 1.00 ^a	0.83, 0.18	1.00 ^a , 1.00 ^a	0.98, 0.31	1.00, 0.58	1.00, 0.70	1.00, 0.58
Hoary bat	0.46, 0.10	0.32, 0.09	0.58, 0.13	1.00 ^a , 1.00 ^a	0.12, 0.06	0.33, 0.09	0.12, 0.06	0.33, 0.09	0.26, 0.08	0.32, 0.08	0.48, 0.11	0.32, 0.08
Northern yellow bat	0.35, 0.09	0.20, 0.07	0.39, 0.10	0.13, 0.06	0.36, 0.09	1.00, 0.44	0.36, 0.09	1.00, 0.44	1.00, 1.00	0.99, 0.35	1.00, 0.88	0.99, 0.35
Cave myotis	0.84, 0.19	0.35, 0.09	0.91, 0.23	1.00 ^a , 1.00 ^a	0.84, 0.20	1.00, 0.44	0.84, 0.20	1.00, 0.44	1.00, 0.95	1.00, 0.67	1.00, 0.97	1.00, 0.67
Evening bat	0.19, 0.07	0	0.18, 0.07	0.25, 0.07	0.27, 0.08	0.83, 0.19	0.27, 0.08	0.83, 0.19	0.35, 0.09	0.18, 0.07	0.47, 0.10	0.18, 0.07
Tricolored bat					0.55, 0.12	0.35, 0.10	0.55, 0.12	0.35, 0.10	1.00, 0.44	1.00, 0.79	1.00, 0.88	1.00, 0.79
Mexican free-tailed bat	0.11, 0.06	0	0.11, 0.05	0	20	5	20	5	20	23	43	23
Sites sampled	20	8	28	5	20	10	20	10	20	23	43	23

^aSome power estimates of 100% are artificially high as a result of using a starting occupancy value of 1 with an SE of 0 for the simulated projections.

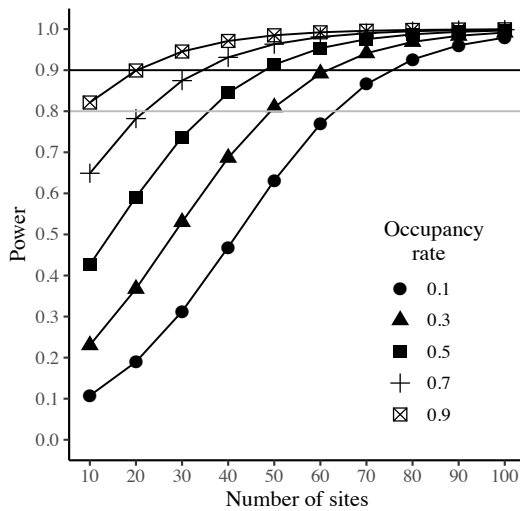


Fig. 3. Sample size calculations from our logistic regression model for the power to detect a 50% decline in occupancy over 25 years projected out to 100 survey sites for monitoring occupancy of bats in our study areas in southern Texas, USA, from data collected in 2015–2017. Individual curves represent various starting occupancy rates, and the horizontal lines represent the benchmark power values of 0.80 (gray) and 0.90 (black).

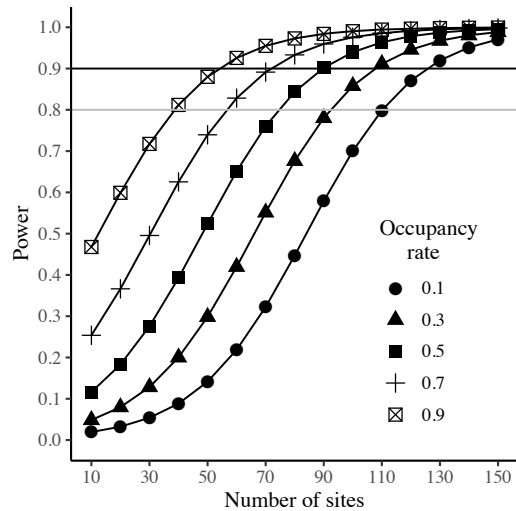


Fig. 4. Sample size calculations from our logistic regression model for the power to detect a 30% decline in occupancy over 10 years projected out to 150 survey sites for monitoring occupancy of bats in our study areas in southern Texas, USA, from data collected in 2015–2017. Individual curves represent various starting occupancy rates, and the horizontal lines represent the benchmark power values of 0.80 (gray) and 0.90 (black).

(*Tadarida brasiliensis*) all contained a quadratic term for ordinal date in the detection probability, suggesting that p changed nonlinearly through the time frame of our sampling (Fig. 2, Appendix 1). Our data showed limited support for models with any variation in p for describing occupancy of tricolored bat (*Perimyotis subflavus*); thus, we assumed the model with a constant p was the most appropriate (Fig. 2, Appendix 1). The resulting occupancy rate estimates from this analysis varied widely among species, sites, and years, including estimates ranging from 0 to 1.0 (Table 2).

Of the 52 data sets used to calculate the power to detect a simulated decline in occupancy, we estimated that 21 (40.4%) of these would result in a power of 0.90 to detect a 50% decline in 25 years and 6 (11.5%) would result in a power of 0.90 to detect a 30% decline in 10 years (Table 3). We estimated the average power to detect a 50% decline over 25 years with the 9 data sets we analyzed for eastern red bat to be 0.95. The same 9 data sets for cave myotis resulted in an average power of 0.81 to detect this change. We had 7 estimates of occupancy for evening bat;

the average estimated power to detect this change for this species was 0.74. Our power estimate for the remaining species was less than 0.60 to detect this change. Average power to detect a 30% decline in 10 years with our data sets was less than 0.50 for all species (Table 3).

The coefficients from our logistic regression models predicting power based on occupancy rate and number of sites sampled indicated that both occupancy rate and number of sites sampled were positively correlated with power for both sensitivities (Table 4). Predictions from these models projected out to 100 sites sampled for detecting a 50% decline in occupancy over 25 years suggest that a power of 0.90 would be reached with approximately 20 sites for populations with a starting occupancy rate of 0.90, but this same power would require over 70 sites for populations with a starting occupancy rate of 0.10 (Fig. 3). Our predictions for detecting a 30% decline in occupancy over 10 years projected out to 150 sites sampled suggest that approximately 55 sites would be required to reach a power of 0.90 for populations with starting occupancy of 0.90, and as many as 125 sites

TABLE 4. Results of logistic regression for (a) power to detect a 50% decline over 25 years and (b) power to detect a 30% decline over 10 years in proportion of sites occupied by individual species of bats from data collected in southern Texas, USA, 2015–2017.

Variable	Regression coefficient (\pm SE)	z	P
(a) Detecting a 50% decline in 25 years			
Intercept	-3.24 ± 1.24	-2.6	0.009
Occupancy rate	4.55 ± 1.33	3.43	<0.001
Number of sites sampled	0.07 ± 0.04	1.71	0.087
(b) Detecting a 30% decline in 10 years			
Intercept	-4.93 ± 1.50	-3.30	<0.001
Occupancy rate	4.75 ± 1.55	3.06	0.002
Number of sites sampled	0.05 ± 0.03	1.62	0.105

may be necessary to reach the same power with a starting occupancy of 0.10 (Fig. 4).

Our second simulation exercise revealed that a CV for occupancy estimates of ≤ 0.21 was required to detect a 50% decline in 25 years with a power of 0.90, and a CV of ≤ 0.07 was required to detect a 30% decline in 10 years. These estimates were constant for the range of occupancy estimates we included in our simulation from 0.10 to 0.90. The mean survey dates of the 10 occasions from each sampled site over our 3 years of sampling fell on ordinal dates 194–198, 245, and 247–250. Our estimation of required sample size based on equation 6.3 from MacKenzie et al. (2006) and our date-specific detection probability estimates showed that populations with smaller occupancy rates require much larger sample sizes to monitor with the same level of sensitivity and power than populations with higher occupancy rates (Table 5). Timing also had the potential to greatly impact required samples sizes, particularly for species with greater variation in detection probability through our sampling time frame. This was most clearly supported by species with peaks in detection probability that did not coincide with our sampling effort (e.g., hoary bat and northern yellow bat; Fig. 2B, C, Table 5).

DISCUSSION

Despite the challenges typically associated with surveying bat populations (e.g., nocturnal, cryptic, and highly vagile; O’Shea et al. 2003), the use of automated acoustic detection and recording equipment and a site occupancy framework provide a robust method for long-term monitoring (Weller 2008, Rodhouse et al. 2012). Furthermore, we showed that it is

possible to reach meaningful power and sensitivity levels for detecting changes in occupancy rates in our study with reasonable sample sizes for 6 of the 7 species we detected, and likely for all 7 if the timing of surveys is adjusted to match periods of higher estimated detection probabilities.

The results from our analyses generally indicated that sample sizes between 50 and 70 sites per study area would be sufficient to reach a power of 0.90 to detect declines in occupancy of 50% over 25 years for most species in our study using 10 nights per site if starting occupancy rates were as low as 0.30. Estimates of required sample sizes to reach the same sensitivity levels were substantially smaller (~ 10 – 20) for populations with starting occupancy rates around 0.70 (Table 5). Our sample size recommendations from the regression modeling (Figs. 3, 4) are slightly more conservative and more appropriate to use as guidelines for other study areas, because these were calculated for unspecified, but typical detection probabilities that we experienced in our study.

Our results suggest that p varied through the season (June–September) for 6 of the 7 species in our study. Similar occupancy studies have found no support for time-varying p , or support for time-varying p for only a limited number of species considered in their studies; however, most of these studies limited their consideration to models describing a linear time trend (Hein et al. 2009, Rodhouse et al. 2012, Bender et al. 2015, Starbuck et al. 2015, but see Yates and Muzika 2006, Pauli et al. 2017). Changes in p over the sampling season may be due to a number of factors, singularly or jointly, including changes in prey availability (Black 1974), juveniles becoming volant (Yates and Muzika 2006), and changing

TABLE 5. Estimated number of sampling sites required to (a) estimate occupancy rates with a CV of 0.21 and detect a 50% decline in occupancy over 25 years with a power of 0.90 and (b) estimate occupancy rates with a CV of 0.07 and detect a 30% decline in 10 years with a power of 0.90 for starting occupancy rates (Ψ) between 0.1 and 0.9, using the mean dates when we collected data (p_{obs}) and the dates associated with the maximum estimated detection probability (p_{max}) for bat species detected on our study areas in southern Texas, USA, 2015–2017.

Ψ	Eastern red bat		Hoary bat		Northern yellow bat		Cave myotis		Evening bat		Mexican free-tailed bat		Tricolored bat	
	p_{obs}	p_{max}	p_{obs}	p_{max}	p_{obs}	p_{max}	p_{obs}	p_{max}	p_{obs}	p_{max}	p_{obs}	p_{max}	p_{obs}	p_{max}
(a) CV = 0.21														
0.1	206	204	421	228	281	205	205	204	207	205	210	206	236	
0.2	92	91	199	103	129	91	91	91	92	91	94	92	107	
0.3	54	53	125	61	79	53	53	53	54	53	55	53	64	
0.4	34	34	88	40	53	34	34	34	35	34	36	34	42	
0.5	23	23	66	27	38	23	23	23	23	23	24	23	29	
0.6	15	15	51	19	28	15	15	15	16	15	16	15	21	
0.7	10	10	41	13	21	10	10	10	10	10	11	10	14	
0.8	6	6	33	9	15	6	6	6	6	6	6	6	10	
0.9	3	3	27	5	11	3	3	3	3	3	3	3	6	
(b) CV = 0.07														
0.1	1853	1840	3789	2050	2533	1845	1846	1838	1863	1842	1891	1851	2128	
0.2	824	818	1792	923	1164	820	821	817	830	819	843	824	962	
0.3	482	477	1127	547	708	479	479	477	485	478	494	481	573	
0.4	310	307	794	360	480	308	309	306	313	307	320	310	379	
0.5	207	205	594	247	343	206	206	204	209	205	215	207	262	
0.6	139	137	461	172	252	137	138	136	140	137	145	139	185	
0.7	90	88	366	118	187	89	89	88	91	88	95	90	129	
0.8	53	51	295	78	138	52	52	51	54	52	58	53	87	
0.9	24	23	240	46	100	24	24	23	26	23	29	24	55	

energy requirements (Barclay 1989). These changes may be adequately described linearly when the time frame is narrow; however, we suggest that nonlinear models are more appropriate, particularly when multiple factors may be involved and over time periods lasting more than a few weeks. Indeed, our data supported a quadratic term for describing changes in p over the season for 4 of the 7 species we detected. If high levels of variation exist in p among surveys, modeling this variation may decrease potential bias in occupancy estimates (MacKenzie et al. 2006). Additionally, by modeling time with a quadratic term, we could identify specific dates that predicted when p would be highest during our sampling. MacKenzie et al. (2006) recommended using sampling techniques that maximize p to attain greater power or reach the same power with less effort. Similarly, timing a study to maximize p should also improve power or reduce required effort, as evidenced by our results. This was most apparent for the hoary bat in our study since our observed p was substantially lower than our predicted p_{\max} later in the season (Table 5, Fig. 2B).

Our results suggest that for eastern red bat, optimal timing for sampling to maximize detection probability occurred from ordinal dates 200 to 240 (20 July–28 August). For species such as cave myotis, evening bat, and Mexican free-tailed bat, optimal timing for sampling occurred from ordinal dates 220 to 260 (8 August–17 September). Furthermore, our predicted efficiency of the sampling time for hoary and northern yellow bats increased through our entire sampling season and may have peaked beyond day 270 (late September). Our estimated p for 4 of the 7 species in our study was <0.2 after the first month of sampling, yet all but 2 of the 7 species reached an estimated maximum p later in the season of 0.39 or greater. According to equation 6.3 from MacKenzie et al. (2006), increasing p^* (probability of detecting the species at least once over all occasions) decreases the sample size required to reach identified targets; however, little improvement was observed for increases in p^* beyond 0.95. MacKenzie and Royle (2005) suggested that a survey strategy that results in a p^* between 0.85 and 0.95 is optimal. With 10 successful occasions, an average of $p = 0.26$ is required to reach $p^* = 0.95$. Our data predicted this was attainable for 5

of the 7 species by initiating sampling after 1 July. Such an initiation date delay would also improve p^* for hoary bat, but not to the 0.95 level. Our estimate of p^* for the mean sampling dates for hoary bat was 0.70; pushing sampling initiation to the end of September would result in $p^* = 0.93$. Our estimate of p^* for tricolored bat was constant through the season at 0.91. While delaying sampling would improve the power of a monitoring program for most species in our study areas, such actions would limit the number of sites that could be visited in a single season with a fixed number of detection units. Furthermore, shortening the sampling duration of a monitoring program may limit its ability to detect temporal patterns in p that may be useful (e.g., for detecting shifts in phenology). If it is not desired or feasible to reach a specific level of p^* for a given species by sampling during the peak period of p or if p is consistently low throughout the sampling season, it may be necessary to increase the duration of sampling to >10 nights per site.

While we set 10 nights per site per year as our goal for the present study, our hardware limitations and our nightly success rate between 80% and 86% resulted in our average of 7.57 nights of sampling. Had we reached 10 successful nights per site, our resulting occupancy estimates would likely have been more precise. Thus, we feel our power estimates are conservative for a monitoring program that achieves 10 successful nights of sampling per site. While our success rates did improve with experience both within and among years, many of the issues we encountered were unavoidable. Hardware for acoustic monitoring of bats has improved greatly in the past decade and will likely continue to become more reliable in the future. However, to those developing monitoring programs with similar equipment, we suggest that they construct plans that allow for success rates similar to ours while still reaching desired sample sizes.

We selected the timing of sampling to focus on summer residents and to avoid migratory bats. Should monitoring of migratory bats be of interest, timing would need to be modified. Similarly, our analysis focused on maximizing efficiency for monitoring all species detected in our study areas. Should monitoring focus on singular or select species among those present, efficacy may be improved by adjusting

the timing of sampling to coincide with the greatest detection probability of those species.

The relationship between our estimates of required sample size and starting occupancy rates is partially due to our use of percent change to define the sensitivity levels. For instance, a 50% decline in occupancy from a starting occupancy of 0.70 represents an absolute change of 0.35, while a 50% decline from a 0.30 occupancy rate represents an absolute change of 0.15. Our high sample size recommendations for low occupancy rates should not deter researchers from initiating a long-term monitoring program. We suggest that sample sizes be selected based on realistic expectations of the sensitivity of a monitoring program balanced with meaningful changes in occupancy rates. We further suggest that long-term monitoring programs include additional conditional protocols, such as increasing sampling intensity when occupancy rates of populations of interest fall below some threshold. Failure to enact these additional protocols would likely result in depleted confidence in estimated occupancy and insufficient power at a point when the information is most critical.

We acknowledge that our use of different versions of classification software among the 3 years of our study represents changes to our methods. Without calibrating these changes, it would be imprudent to infer changes in occupancy rates from our data. However, we do not believe these changes affected our results or conclusions regarding sample sizes and power from the present study because we were not testing for occupancy changes; we simply used our resulting occupancy estimates as starting points for simulated declines in our power analyses. We strongly encourage researchers and managers to use new technologies and software that improve bat detection and call classification in their long-term monitoring programs. However, it is critical to calibrate changes to methods (such as our use of different software versions) to account for potential bias that may otherwise be interpreted as population changes. Finally, automated classification should be considered an assistive technology to direct the user to files for manual confirmation. When used properly, manual oversight of the automated classification should minimize any effect from differences in software versions.

MANAGEMENT IMPLICATIONS

For monitoring bat population occupancy rates, we recommend incorporating nonlinear terms for time-varying p in occupancy models with sampling periods lasting more than a few weeks. If the temporal pattern in p is better described with a linear relationship, or if data are insufficient to support a more complex model, these nonlinear models will not be well supported by the data and will not be selected by typical information theoretic approaches. However, as we point out above, considering potentially complex time effects should allow researchers the opportunity to improve power or reduce the required sample size by adjusting the timing of their sampling to coincide with higher rates of p . Additionally, modeling temporal changes in p each year should also provide the means for detecting shifts in phenology, such as timing of migration and reproduction, which are likely to result from climate change (Jones et al. 2009, Stepanian and Wainwright 2018).

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APPENDIX 1. Highest supported occupancy model based on AICc score, relative model weight (W_i), and resulting estimated detection probability (p) and associated standard error (SE) for our median sampling date of 30 July (ordinal date 211) for the 7 species of bats detected in southern Texas, USA, in 2015, 2016, and 2017. We fit 3 models to each species' data set: model $p(t^2)$ included a quadratic term for ordinal date in p ; model $p(t)$ included a linear term for ordinal date in the detection probability; and model $p(\cdot)$ included no covariates for p . All 3 models included a group covariate for occupancy based on our study areas.

Species	Common name	Selected model	W_i	p	SE
<i>Lasiurus borealis</i>	Eastern red bat	$p(t^2)$	1.00	0.47	0.035
<i>Lasiurus cinereus</i>	Hoary bat	$p(t)$	0.68	0.08	0.027
<i>Lasiurus intermedius</i>	Northern yellow bat	$p(t)$	0.79	0.07	0.034
<i>Myotis velifer</i>	Cave myotis	$p(t^2)$	1.00	0.45	0.035
<i>Nycticeius humeralis</i>	Evening bat	$p(t^2)$	0.90	0.34	0.034
<i>Perimyotis subflavus</i>	Tricolored bat	$p(\cdot)$	0.30 ^a	0.21	0.044
<i>Tadarida brasiliensis</i>	Mexican free-tailed bat	$p(t^2)$	0.85	0.30	0.037

^aModel $p(t^2)$ for tricolored bat had a W_i of 0.59; however this model included 2 more parameters than model $p(\cdot)$ and an AICc score that was lower by only 1.34 units.