



Development of Multispecies, Long-Term Monitoring Programs for Resource Management[☆]

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ABSTRACT

There is growing interest among resource managers in implementing long-term wildlife monitoring. The process to develop such a program may seem daunting, however, because it requires determining the species, metrics, sampling methods, experimental design, and level of effort necessary to achieve the desired power for detecting meaningful changes. Failure to give these decisions proper attention often leads to suboptimal information for decisions and planning objectives. Our primary objectives were to develop alternative scenarios for a monitoring program, including power estimates and sampling effort required to detect population changes for small mammals on rangelands in southern Texas. Our secondary objective was to present a framework for developing customized monitoring programs for tracking wildlife populations over time. We trapped small mammals using ~28 000 trap nights each year from 2014 to 2016 resulting in 13 183 captures of nine species. We estimated abundances and occupancy in each year for each species and conducted power analyses using simulations. We used these results to develop four multispecies monitoring scenarios: two with distinctly different levels of effort with abundance as the focal metric and two for monitoring occupancy. The most effort-intensive scenario required trapping 40 grids for 6 consecutive nights each yr. With this effort, we predicted it would be possible to detect annual changes in abundance of $\leq 10\%$ after 10 yr for four species and net declines in occupancy of $\leq 50\%$ after 10 yr for five species with a power of 0.90. The least effort-intensive scenario required trapping 30 transects for 4 consecutive nights each yr. We predicted this effort would allow for the detection of annual changes in occupancy rates between 35% and 55% after 10 yr for five species. Our study is an example for land managers, providing general guidelines for developing rigorous, long-term monitoring programs specific to their objectives.

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Introduction

There is growing interest among resource managers in implementing long-term wildlife monitoring programs. Data from monitoring have substantial value for detecting relationships between management actions and animal populations (Pollock et al., 2002) and should provide direction regarding future management decisions (Nichols and Williams, 2006; Kendall and Moore, 2012). In addition, monitoring that is not otherwise driven by a specific hypothesis can help researchers understand impacts of unplanned events such as weather (short term) and climatic patterns (long term) on wildlife populations (Beever and Woodward, 2011; Fancy and Bennetts, 2012; Johnson, 2012). However, formal processes necessary to implement a

monitoring program may seem daunting. Proper planning and implementing of a monitoring program includes identifying an appropriate species or taxa (Carignan and Villand, 2002), selecting metrics that are sensitive to changing conditions (Williams et al., 2002), selecting sampling methods that best maximize efficiency (Garton et al., 2005), using an experimental design to isolate the hypothesis of interest (e.g., change detection) with the most efficient probabilistic sampling (Garton et al., 2005; Morrison et al., 2008), and employing sufficient effort (sample size) to achieve the desired level of power for detecting biologically meaningful changes (Fig. 1; Williams et al., 2002; Field et al., 2007). Failure to give these decisions proper attention often leads to misallocated resources, resulting in suboptimal information for decisions and planning objectives (Yuccoz et al., 2001; Legg and Nagy, 2006). In addition, incorporating statistical power analysis into program design can ensure sampling efforts are optimized such that more effort than is required to meet stated objectives is not used (Lenth, 2001; Reynolds et al., 2011). Considering the complexities of the relationship among sampling objectives, experimental designs,

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Developing a Multispecies Wildlife Monitoring Program

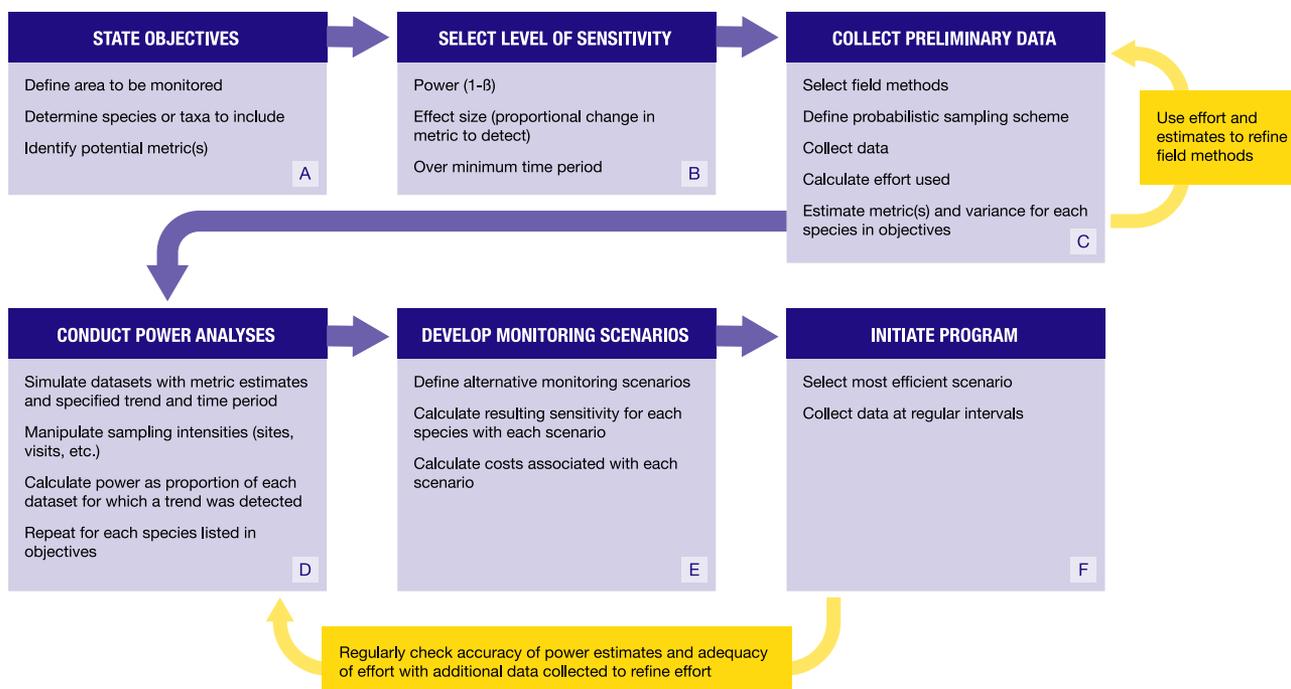


Figure 1. Framework for developing a customized, multispecies monitoring program. If prior data that were collected using methods proposed for the monitoring program already exist, it may not be necessary to collect additional data. However, preliminary data should also be specific to and representative of the spatial location of the proposed monitoring program.

power, and effort, it is also cost effective to evaluate and compare alternative monitoring scenarios.

Our primary objectives were to 1) develop and evaluate alternative monitoring scenarios focused on detecting spatial-temporal changes in species or assemblage of small mammals within a rangeland system, 2) estimate power and sensitivity for our proposed monitoring scenarios, and 3) characterize appropriate sampling effort required and resulting level of sensitivity for each scenario. Our secondary objective was to present a framework that can be replicated elsewhere for developing customized monitoring programs for tracking wildlife populations over time.

Step 1. State Objectives

The first step in developing a monitoring program requires identification of details that will define the focus of the program and guide further decisions. This includes defining the spatial area of interest, the species or taxa to monitor, and the state variable(s) of the species to measure (Fig. 1A).

Define the Area

The appropriate spatial area for developing a monitoring program should be explicit from the program's objectives (Olson et al., 1999). The objectives for our study specified the ranches owned by the East Foundation as the area for our monitoring program. The East Foundation is composed of approximately 87 000 ha of rangeland in southern Texas that is managed as a working laboratory to support wildlife conservation, private land stewardship, and other public benefits associated with ecologically sound cattle ranching (Fig. 2). We collected data on the 60 752-ha San Antonio Viejo (Jim Hogg and Starr Counties) and 10 984 ha El Sauz (Willacy and Kenedy Counties) ranches. Annual precipitation averages for the period of 1981–2010 ranged from ~57 cm at the

San Antonio Viejo Ranch to ~66 cm at the El Sauz Ranch (NOAA, 2016). Annual weather patterns were highly variable in southern Texas, with rainfall totals over the 12-mo periods ending 30 April 2014, 2015, and 2016 on the San Antonio Viejo Ranch of 47.3 cm, 59.8 cm, and 49.1 cm, respectively. Rainfall totals for the same periods for the El Sauz Ranch were 52.6 cm, 94.9 cm, and 72.2 cm, respectively.

The San Antonio Viejo Ranch was a matrix of woodland (73%) and shrubland (18%), 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). El Sauz was located 117 km to the east of San Antonio Viejo 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 El Sauz 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).

Select Monitoring Taxa

Selection of an appropriate focal species or group to monitor depends on the program's objectives (Yuccoz et al., 2001; Wiens et al., 2008). Monitoring for a specific species of concern, to detect impacts of management actions, or as an indicator of biodiversity or ecosystem process would likely all result in selecting different focal species (Caro and O'Doherty, 1999). We assume the objectives have been clearly stated, including identification of the monitoring species, before the development phase that our paper attempts to address. Thus, we limit our coverage of concepts that should be considered when selecting a focal species or taxa to a brief summary. When the focal species is not explicitly identified in the objectives, a number of criteria have been identified to help guide the decision, such as species that can be monitored

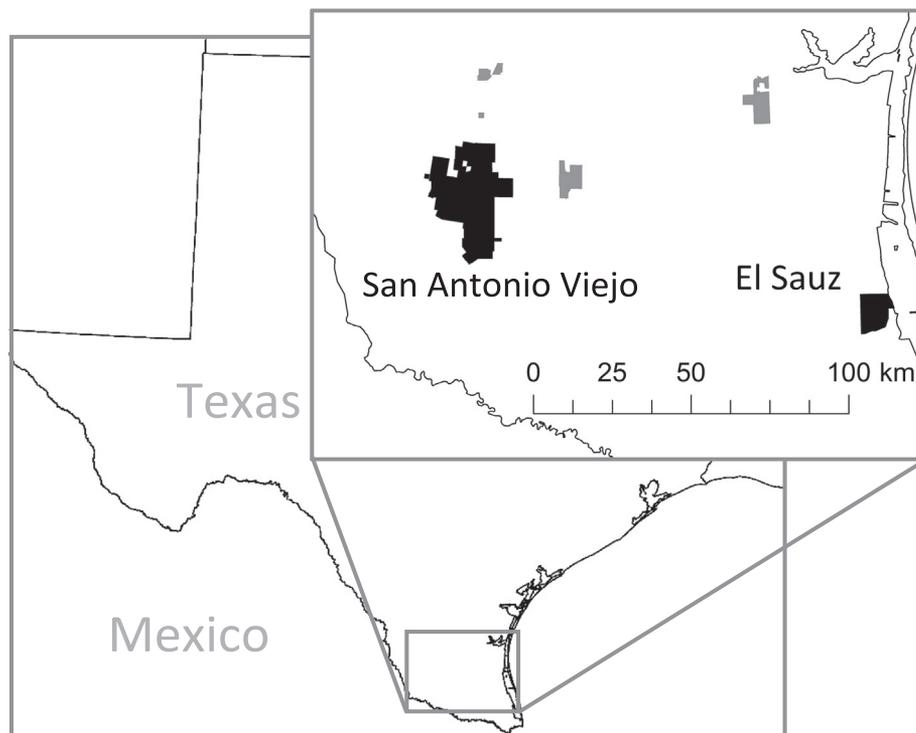


Figure 2. Ranches where we collected data (black shapes) used to develop long-term monitoring scenarios for the small mammal assemblage for the East Foundation (black and gray shapes) in southern Texas, USA, 2014–2016.

efficiently, are sensitive to stresses, respond predictably with low variability in the response, indicate the cause of the observed change, and will facilitate reliable prediction of other species' or systems' response (Noss, 1990; Kremen, 1992; Hilty and Merenlender, 2000; Block et al., 2001; Carignan and Villand, 2002). When possible, target species whose detected trends are likely to be used to guide future management or evaluate past decisions should be selected (Kremen, 1992; Noon et al., 2012). In addition, if monitoring results are to be used to guide future management aimed at reducing population loss, Wilson et al. (2015) suggest placing higher values on species with an unknown population trend and whose response will possibly incite a reallocation of resources to address a detected decline.

Multiple species monitoring has the advantage of potentially including species with a broad range of life history traits such that individual species may respond differently to changing conditions (Carignan and Villand, 2002). Collectively, multiple species monitoring has a greater probability of detecting change within the system, as opposed to an equivalent amount of effort monitoring only a single species (type II error). For instance, complex assemblages of birds, small mammals, and reptiles have likely evolved to reduce niche overlap through partitioning of resources such as diversification of food preference (Grinnell, 1904). In rangeland systems, small mammal assemblages often include five or more species from three or more families, representing up to three trophic levels (French et al., 1976; Hoffmann and Zeller, 2005; McAdoo et al., 2006; Galetti et al., 2016). As such, multiple species monitoring efforts can provide management insights and inferential linkages to other system changes that would otherwise be missed in single-species monitoring efforts. In certain situations, increasing the number of focal species to be monitored can be done without significantly increasing the effort required, further improving the appeal for monitoring multiple species.

For the present study, we developed monitoring scenarios for the small mammal assemblage present in our study area. To optimize the balance between information gained and effort required, we specifically defined our focal taxa to include extant species for which populations can be reasonably monitored with standard live-trapping methods

using box-style (i.e., Sherman) traps at night. Use of small mammal species as monitoring foci can be valuable for understanding spatial-temporal variation in rangeland systems (Rosenzweig and Winakur, 1969; Germano and Lawhead, 1986; Kerley, 1992; Carignan and Villand, 2002). Small mammals represent an important trophic level in rangeland systems, transferring energy from primary producers to a vast array of secondary and tertiary consumers. Small mammals make up a significant portion of the diet of numerous raptors (Littles et al., 2007; Behney et al., 2010; Strobel and Boal, 2010; Williford et al., 2011), snakes (Pisani and Stephenson, 1991; Stevenson et al., 2010), and medium-sized mammals (Cypher, 2003; Lindzey, 2003; Melville et al., 2015). Many small mammal species also cache seeds and fruits for later consumption, assisting in dispersing specific shrubs and potentially influencing the plant community (Ryszkowski, 1975; Price and Jenkins, 1986; Ostfeld and Clay, 2002). Further, small mammals have a short generation time and high potential reproductive output, allowing these species to respond quickly to perturbations in rangeland systems (Abramsky, 1978; Doonan and Slade, 1995). Because small mammals are nonmigratory with limited ranges and dispersal (Haskell et al., 2002; Tucker et al., 2014), demography should reflect localized conditions and therefore provide a representative sample of spatial variability in microhabitat conditions (Gleason, 1926).

Select Monitoring Metrics

Monitoring metrics should provide a precise and unbiased estimate of a particular population or community state with a practical amount of sampling effort (Block et al., 2001; Morrison et al., 2008). Moreover, the spatial and temporal resolution of the monitoring metric should be such that detected changes in the metric may be addressed with pragmatic management actions. The most important criteria for monitoring metrics are their ability to meet the objectives of the monitoring program. For instance, if the purpose of monitoring is to assess wildlife response to ecological restoration efforts, Block et al. (2001) argue that population dynamics should be used as the metric. However, metrics such as

species richness, nest success, or those associated with phenology may be most appropriate for other monitoring objectives and target species.

Because population size is so often the metric used for detecting ecological effects of management actions (Block et al., 2001; Williams et al., 2002), many methods have been developed for comparing relative abundance between sites or through time with the use of indices. However, use of indices requires assumptions that are often biologically unrealistic, resulting in biased estimates that are unreliable for monitoring purposes (Anderson, 2001; MacKenzie and Kendall, 2002). Unbiased methods for estimating abundance that account for imperfect detection are more appropriate for monitoring and can be accomplished for small mammals with mark-recapture data (Pollock et al., 2002; Williams et al., 2002; Chao and Huggins, 2005). The resulting estimates are that of abundance for the effective sampling area, which is determined by the trap configuration used for sampling and is specific to each species. For monitoring purposes, the effective sampling area does not need to be defined, so long as it does not change during the life of the monitoring program.

Unbiased abundance estimation is effort intensive, often prohibitively so for large-scale monitoring programs, thus reducing its effectiveness as a monitoring metric option (McKelvey and Pearson, 2001). In addition, detecting change in abundance is not always the desired monitoring goal. Conversely, occupancy can be used as an alternative monitoring goal and usually requires substantially less sampling effort than abundance estimation (MacKenzie et al., 2002). Occupancy is defined as the proportion of sites occupied by a particular species regardless of its abundance at any time (MacKenzie et al., 2006). Analogous to abundance estimation with mark-recapture data, unbiased methods exist for estimating occupancy that account for imperfect detection (MacKenzie et al., 2006). The resulting estimates are made at broad spatial scales (generally estimated as a proportion of all sites sampled) and thus, occupancy estimates are not applicable to the same spatial scale changes as abundance estimates (estimated for individual sites). We evaluated estimators of abundance and occupancy to illustrate complementary strengths and weaknesses of each when used in a longitudinal spatial-temporal monitoring program.

Step 2. Select Level of Sensitivity

Power, Effect Size, and Time Period

The next set of decisions that managers need to make will determine how sensitive the monitoring program will be to change, which also dictates the level of effort that will need to be invested into data collection. The sensitivity of a monitoring program is defined by power, effect size, and time period (Fig. 1B). Power is defined as 1 minus the probability of failing to detect a change of given effect size when one occurs, where effect size is the minimum change expected to be detected over a defined time period. Defining the sensitivity of a single-species monitoring program is rather straightforward (e.g., 90% probability of detecting a 30% decline that occurs over 5 yr). When considering multiple species, a minimum level of sensitivity might be set as a target to reach for all or a specified number of species included in the monitoring program.

If all of the decisions that determine the level of sensitivity are made a priori, the subsequent steps in the process of program development will be simplified. However, as is often the case, these decisions may depend on final estimation of program costs. In such cases, it is useful to develop multiple monitoring scenarios that represent a range of sensitivities. The directive for our monitoring program development did not include sensitivity specifics; thus, we developed monitoring scenarios that represent a range of effect sizes, time periods, and implementation costs. We considered three time periods for evaluating power. We selected 3 yr as this represented a duration that might capture a response to a short-term impact (e.g., wet year or management action). We expected 5-yr monitoring durations to begin to disentangle trends from responses to short-term weather patterns but potentially identify

significant trends quick enough to respond through management decisions and 10-yr monitoring durations to be able to detect trends despite longer-term weather phenomena (e.g., a 4-yr drought). We selected a single level of power to keep the number of scenarios to evaluate at a manageable number. A commonly used value for power in statistical studies is 0.80 (Cohen, 1992; Lenth, 2001); however, we selected a power of 0.90 as we intended to keep the probability of failing to detect changes at or below 10% in our recommendations.

Step 3. Collect Preliminary Data

Preliminary data are critical for developing a monitoring program in that they allow the researcher to determine the level of effort required to meet stated objectives with the selected level of sensitivity. Required effort may be determined from preexisting data; however, the preliminary data should be collected using similar methods such that precision of estimated metrics is representative of what is expected from the proposed program. Similarly, spatial variation in preliminary data should also be representative of what is expected for the spatial extent of the population to be monitored. Thus, field methods must be selected before preliminary data can be collected (or identified from previous efforts). As is the case with any field study or monitoring program, initial sampling methods should be based on past experience and a thorough review of relevant literature to collect data to best meet stated objectives. However, a well-designed pilot study should identify opportunities for comparing and refining methods to improve efficiency (Fig. 1C). This will likely require additional design considerations not typically included in actual monitoring programs, such as using multiple methods for capturing or detecting individuals, and including measures of effort associated with each observation or capture (e.g., time of each observation during a timed point count, distance traveled for each observation during transect surveys). Such ancillary data will allow for direct comparisons among methods and determine optimal within-sampling effort (e.g., duration of each sample, length of sampling transect) to balance the desire to reach a specified detection or capture probability with the need to sample a particular number of sites that becomes apparent after a power analysis is conducted. Because we were unaware of any data that met the requirements outlined earlier for the small mammal assemblage in our study area, we planned and executed a pilot study based on a literature review and the collective experience of our research team.

Select Field Methods

The optimal field methods for a monitoring program will depend on a number of factors, including the focal species or taxa, and the selected metrics. Managers should select methods that maximize the data required for metric estimation while minimizing effort (Field et al., 2005). We identified large ($7.6 \times 9.5 \times 30.5$ cm, model XLK) and extralarge ($10.2 \times 11.4 \times 38$ cm, model XLF15) Sherman live traps (H. B. Sherman Traps, Inc., Tallahassee, FL) as effective for the focal species for our monitoring program. Our target assemblage of small mammals excluded extant species of squirrels (family Sciuridae) and pocket gophers (family Geomyidae). We excluded squirrels from consideration because those present on the study sites were diurnal and, therefore, would have required a different strategy for monitoring than the other species. Similarly, we excluded pocket gophers since they were almost exclusively fossorial and would have required trap modifications and special trap placement to monitor. If the objectives of a monitoring program included populations of these or similar species, such as shrews (family Soricidae), additional trapping methods would need to be incorporated.

Trap Configuration

We recognized that our selected metrics of abundance and occupancy may be more efficiently monitored with distinct trap

configurations. Square grids with modest spacing (10–20 m between traps) are typically used for estimating abundance in small mammal studies as they provide acceptable levels of recapture rates for most species (Nichols and Pollock, 1983). For species detection and occupancy modeling, long transects with wider trap spacing may be preferred as they are more likely to encounter a greater diversity of vegetation, which in turn should increase diversity detected (Caughley and Sinclair, 1994; Krebs, 2009). Because we were interested in both abundance and occupancy as potential monitoring metrics, we attempted to use an equal number of square grids and elongated transects each year.

We modified trap configurations across years of our study in an attempt to refine our field methods. We varied our trap station configuration between 11×11 and 13×13 with 15–20 m spacing (3.24–4.4 ha grids; Bowman et al., 2001; Manley et al., 2006). To accommodate larger-bodied individuals, we also placed an extralarge Sherman trap at every second to third station. On the transects, we used trap configurations of 11×4 , 15×3 , and 19×3 with 25-m spacing (1.75–2.25 ha transects). We also placed extralarge traps at 50–75 m spacing along the outer transects.

Trapping Protocol

We placed traps unopened and not baited, 3 nights before trapping to allow individuals to become accustomed to the traps (Chitty and Kempson, 1949). We positioned traps near habitat features that could be used as cover along travel corridors within 2 m of the grid point and covered traps with local substrate (Jones et al., 1996). Beginning the afternoon before the first trap night, we opened and baited traps and checked and closed them each morning. When setting traps, we baited each with a teaspoon (4.9 mm³) of peanut butter and rolled oats mixture prepared in a 4:1 ratio by weight and provided a 2.54×2.54 cm Nestlet (Ancare) for bedding material. Nestlets are squares of pulped cotton that can be shredded into bedding by captive animals and are commonly used in laboratory settings. The minimum number of nights of trapping for mark-recapture analyses is 2; however, each additional night of trapping adds data that can improve estimates as long as population closure can be assumed (White et al., 1982). To ensure we had sufficient data to evaluate tradeoffs between intensity of trapping at a single site and number of sites trapped, we trapped each site for 6 nights. Most often, this occurred over consecutive nights; however, we suspended trapping when overnight temperatures were forecasted below 4°C or the probability of precipitation was > 50%. Such breaks in trapping do not affect estimates so long as the population can be assumed to be closed from the first to the last day of trapping (White et al., 1982). We identified the species of each individual captured. However, we combined two pairs of species into species groups due to difficulty with field identification: Ord's kangaroo rat (*Dipodomys ordii*)/Gulf Coast kangaroo rat (*Dipodomys compactus*) and hispid pocket mouse (*Chaetodipus hispidus*)/Mexican spiny pocket mouse (*Liomys irroratus*). We marked each individual with a pattern of four spots using blue, green, purple, and red markers to create a unique identification on the ventral surface below the neck (Root et al., 1999).

Define Probabilistic Sampling Scheme

Use of a probabilistic sampling scheme is critical to ensure that spatial variation is not underrepresented in preliminary data, which would result in power estimates that are biased high. In addition, probabilistic sampling ensures that population changes can be inferred from changes detected by the monitoring program (Morrison et al., 2008). We used stratified random sampling to select our trapping locations for collecting our preliminary data. We created preliminary strata by using a Global Information System (GIS) vegetation layer of predominant species, physiognomic structure, and functional habitat similarity separately for each ranch (McLendon et al., 2013a, b). This resulted in 8 strata for the El Sauz Ranch and 10 strata for the San Antonio Viejo Ranch. We then allocated our sampling efforts proportional to the

relative area of each stratum, with a minimum of two sampling sites assigned to each stratum on each ranch. We randomly selected sampling locations within strata with a minimum buffer of 100 m from the edge to minimize influence of adjoining strata. We modified our sampling effort (number of sites trapped and trap configuration) each year in order to optimize effort; however, we attempted to sample the same sites in successive years to isolate interannual variation. Each year, we systematically assigned the order in which we sampled each site to reduce travel time but were careful to avoid within-season, temporal clustering of sampling sites of a given stratum.

Collect Data

We captured animals from mid-January to mid-April 2014–2016. We trapped small mammals on a total of 61 transects and 59 grids over the 3 years of the study and detected 11 species or species groups (Table 2). Detections were inconsistent and captures extremely low for marsh rice rat (*Oryzomys palustris*) and roof rat (*Rattus rattus*); therefore, we excluded these species from consideration in our monitoring program development.

Calculate Effort Used

In addition to collecting data specified by the chosen metrics, it is also critical to calculate the effort required to do so. These additional data allow for accurately assigning costs to specific monitoring scenarios, as well as refining field methods for optimizing efficiency. We recorded the number of field technicians and total time required to establish, check, and remove trapping grids and transects throughout our study. We also calculated time necessary for commuting and data entry associated with a single sampling site. We calculated effort cost estimates using our technician costs from 2016. Specifically, we paid technicians \$2 000/mo, which translated to direct costs of \$3 100/mo, or about \$19.38/hr.

Estimate Metrics and Variance

The final step before conducting a power analysis is to estimate metrics and associated levels of variance relative to the effort used in collecting the preliminary data. These estimates should be generated using the same methods and models that are proposed for the actual monitoring program for an accurate assessment of power.

Abundance

We used the 6-d capture histories of individuals of each species for estimating abundance on individual sites in Program MARK using the Huggins' *p* and *c* model (White and Burnham, 1999). Failure to account for variation in capture probability generally results in biased estimates of abundance (Otis et al., 1978; Chao and Huggins, 2005). We accommodated potential behavioral responses in our candidate set of models by using a behavioral model as our base model that allows probability of first capture (*p*) to differ from probability of recapture (*c*; White et al., 1982). Neophobia is a term used to describe the response of certain species that avoid unfamiliar features, such as a trap, but become more likely to enter the trap with each day of trapping. Although our placement of traps 3 days before the beginning of trapping was an attempt to minimize the effects of neophobia, we did not assume these efforts were entirely successful. Thus, we allowed for the potential of neophobia by including a term for a linear time trend in *p* in our candidate set of models. We also hypothesized that the square grids with narrower trap spacing would result in different *p* and *c* than the transects with wider trap spacing by including models with a term for grid shape in *p* and models with a term for grid shape in both *p* and *c*. This resulted in a set of six candidate models that we fit to each species' dataset for each year (Table 1).

Table 1

Candidate set of models and associated number of parameters (k) for estimating population abundance and occupancy rates for small mammals from data collected in 2014, 2015, and 2016 on East Foundation lands, southern Texas, United States. Abundance model parameters are probability of first capture (*p*) and probability of recapture (*c*). Occupancy model parameters are probability of detection ($p_{\text{detection}}$) and probability of occupancy (ψ). Covariates are linear time trend (T) and trap configuration (shape). The latter was a grouping covariate for individuals captured on grids or transects.

Abundance models	k	Occupancy models	k
<i>p</i> (T + shape), <i>c</i> (shape)	5	$p_{\text{detection}}$ (T + shape), ψ (.)	4
<i>p</i> (T + shape), <i>c</i> (.)	4	$p_{\text{detection}}$ (T), ψ (.)	3
<i>p</i> (shape), <i>c</i> (shape)	4	$p_{\text{detection}}$ (shape), ψ (.)	3
<i>p</i> (shape), <i>c</i> (.)	3	$p_{\text{detection}}$ (.), ψ (.)	2
<i>p</i> (T), <i>c</i> (.)	3		
<i>p</i> (.), <i>c</i> (.)	2		

We used model averaging based on weights from Akaike’s Information Criterion adjusted for small sample sizes (AIC_c) to generate an estimate of abundance and associated SE for each species at each site trapped, treating sites trapped in multiple years as independent samples (Burnham and Anderson, 2002). We removed models that resulted in poorly estimated parameters (typically estimates of $P < 0.001$ and abundance > 10 000) before model averaging. While these models generally garnered extremely low AIC_c weights, the resulting abundance estimates were many magnitudes greater than what is biologically possible and have the potential to greatly bias model averaged estimates. If a minimum of three models were not remaining after model censoring, we concluded that the data were too sparse for model fitting and discontinued analysis of the specific subset of the data. We used the unconditional SE reported by Program MARK, which accounts for both the weighted variance conditional on each model in the candidate model set, and variance associated with model uncertainty (Burnham and Anderson, 2002). We conducted multimodel inference using data from the first 4, 5, and all 6 d of trapping separately to generate abundance and variance estimates for each duration and species combination.

Kangaroo rats were uncommon in 2014, with a total of 33 captures at six separate sites (Table 2). These data were insufficient for estimating abundance; however, we did obtain sufficient captures for estimation in 2015 and 2016. We used the average estimates from the 2015 and 2016 data for determining power for monitoring abundance for kangaroo rats.

We were unable to fit a minimum of three abundance models to the pocket mice dataset in 2016, and many of the estimates from 2014 and 2015 were extremely imprecise. We assumed these issues were due to high heterogeneity in *p* caused by grouping species that likely varied in

Table 2

Number of total captures of 11 species or species groups captured on square grids (S) and rectangular transects (R) in 2014, 2015, and 2016 on East Foundation lands, southern Texas, United States. Sites sampled refers to number of grids and transects we used in each yr of the study.

Species	2014			2015			2016		
	S	R	Total	S	R	Total	S	R	Total
Northern pygmy mouse	282	91	373	68	43	111	100	30	130
Pocket mice ¹	484	110	594	388	158	546	82	54	136
Kangaroo rats ²	12	21	33	281	161	442	214	84	298
Southern Plains woodrat	109	5	114	139	69	208	307	115	422
Northern grasshopper mouse	536	133	669	817	533	1350	67	77	144
Marsh rice rat	1	0	1	0	2	2	0	0	0
White-footed mouse	890	434	1324	1623	862	2485	631	343	974
Merriam’s pocket mouse	467	96	563	148	59	207	59	11	70
Roof rat	0	0	0	0	0	0	24	7	31
Fulvous harvest mouse	48	36	84	225	69	294	59	19	78
Hispid cotton rat	385	53	438	174	41	215	516	364	880
Sites sampled	15	11	26	22	28	50	22	22	44

¹ Includes captures of hispid pocket mice and Mexican spiny pocket mice.

² Includes captures of Ord’s kangaroo rats and Gulf Coast kangaroo rats.

relative abundance at each site, as well as their propensity to enter a trap. Therefore, we did not run power analysis for estimating abundance for these species and we excluded this group from further consideration for monitoring abundance. We were also unable to fit a satisfactory number of models to Merriam’s pocket mouse (*Perognathus merriami*) and grasshopper mouse (*Onychomys leucogaster*) datasets from transects in at least 1 yr and so only conducted power analyses for abundance estimation for these species using data from square grids.

Considering the complete set of data, white-footed mice (*Peromyscus leucopus*) had the greatest estimated abundance on grids and transects (31.8 and 22.7, respectively; Table 3, Fig. 4). Southern Plains woodrat (*Neotoma micropus*) had the lowest estimated abundance on grids, with 11.3 individuals, and fulvous harvest mice (*Reithrodontomys fulvescens*) had the lowest estimated abundance on transects, with 4.7 individuals. In general, the abundance estimates had substantially improved coefficient of variation (CV) with the complete set of 6 d than with data of shorter durations. The exceptions were for northern pygmy mouse (*Baiomys taylori*) on both trap configurations and Merriam’s pocket mouse on grids; CV were lower using 5 d of trapping. In addition, data from grids generally resulted in abundance estimates with lower CV than data from transects. We used these results to select 6 d of trapping using square grids for estimating power and making recommendations for monitoring both abundance and occupancy simultaneously.

Occupancy

We used the record of detections at each sampling site over the 6-d trapping period for a given species to estimate site occupancy rates (ψ) and detection probabilities using single-season occupancy models in Program MARK (White and Burnham, 1999). Detection probability ($p_{\text{detection}}$) is defined as the probability of detecting an individual of a particular species, given it occupies the sampling site. We assumed the different trap configurations would have minimal impact on whether a site was occupied by a particular species, but because of the differences in the number of traps used, they may affect the $p_{\text{detection}}$. Therefore, we included a term for grid configuration in $p_{\text{detection}}$. Neophobia is known to affect the probability of individuals entering traps, and particular species appear to be more prone to it than others (Faust et al., 1971). It is intuitive, therefore, to assume that neophobia may also result in a time trend in $p_{\text{detection}}$ in occupancy studies. To account for this potential source of variation, we also included a term for describing a linear trend in $p_{\text{detection}}$ associated with trap day. We considered the global model with terms for trap configuration and a linear time trend to describe variation in $p_{\text{detection}}$, and all three possible reduced models in our candidate set of models (see Table 1).

We used model averaging based on AIC_c weights to generate an estimate of ψ and associated unconditional SE for each species in each year (Burnham and Anderson, 2002). We then averaged these estimates across all 3 yr of data and repeated these steps using only the first 5 d of trapping, first 4 d of trapping, and again, using only the first 3 d of trapping to generate separate estimates from 3, 4, 5, and 6 d of trapping for monitoring occupancy.

We used capture data for nine species to estimate annual occupancy rates and associated unconditional SE for each year with the various trapping durations and then averaged these values across all 3 yr (Table 4). Average estimated occupancy rates were lowest for the northern pygmy mouse and highest for the white-footed mouse, with proportion of sites occupied for northern pygmy mouse ranging between 0.21 and 0.25 and for white-footed mouse ranging between 0.81 and 0.84, depending on the number of days of trapping data used. In general, occupancy estimates increased only slightly with the addition of each day of trapping data. The exception was Merriam’s pocket mouse, which had a reduction in estimated occupancy rates with additional days of data after 4 d (from 0.63 to 0.61). We used these results, along with the relatively stable estimates of SE with various days of trapping to select 4 d of trapping for determining power and

Table 3
Average estimates for abundance (\hat{N}), standard deviation (SD), coefficient of variation (CV), and the average number of square grids (S) and rectangular transects (R) estimates were derived for (n) each year on East Foundation lands, southern Texas, United States. Blanks indicate data were insufficient for generating useful estimates.

Species	Trap config.	Days of trapping											
		4				5				6			
		\hat{N}	SD	CV	n	\hat{N}	SD	CV	n	\hat{N}	SD	CV	n
Northern pygmy mouse	S	40.2	403.5	10.05	4.3	18.1	4.0	0.22	4.7	22.4	6.5	0.29	5.0
	R	8.1	9.9	1.22	4.3	7.8	2.0	0.25	4.7	9.1	2.4	0.26	4.7
Kangaroo rats ^{1,2}	S					17.9	26.5	1.48	12.5	14.1	10.4	0.74	12.5
	R					11.8	15.5	1.32	9.5	9.2	8.5	0.91	10.5
Southern Plains woodrat	S					10.4	12.3	1.18	13.7	11.3	8.7	0.77	14.3
	R					25.5	241.0	9.46	10.3	11.2	22.6	2.01	10.3
Northern grasshopper mouse	S	12.4	15.3	1.24	14.0	13.4	11.8	0.89	14.0	14.4	11.3	0.79	14.0
	R												
White-footed mouse	S					29.6	57.7	1.95	17.0	31.8	44.2	1.39	17.0
	R					23.9	180.1	7.55	16.0	22.7	51.1	2.25	16.3
Merriam's pocket mouse	S					16.0	21.8	1.37	12.3	25.7	100.1	3.89	13.0
	R												
Fulvous harvest mouse	S									11.6	17.2	1.48	8.7
	R									4.7	7.7	1.63	7.7
Hispid cotton rat	S	23.4	14.2	0.61	6.0	28.3	14.5	0.51	6.7	29.5	5.0	0.17	6.7
	R	13.4	67.3	5.00	5.3	19.4	16.1	0.83	5.0	19.0	4.4	0.23	7.0

¹ Combined estimates for Ord's kangaroo rat and Gulf Coast kangaroo rat.

² Data were averaged from 2015 and 2016 only.

making recommendations for monitoring occupancy in the absence of monitoring abundance.

Refine Field Methods

Examination of preliminary data, including calculations of associated effort, allows researchers the opportunity to optimize their sampling effort for the final monitoring scenario designs (Fig. 1C –feedback loop). In our example, we used preliminary data to maximize effort with respect to trap configuration and seasonal timing.

Trap Configuration

We recorded the start and end times for each day of trapping at each site and altered the trap configuration from the previous yr's effort in an attempt to optimize the balance in area sampled and time required to check traps and process animals.

Seasonal Timing

We attempted to identify and define patterns in captures across each trapping season for each species of small mammal in order to optimize sampling effort and to provide meaningful recommendations of timing of trapping for long-term monitoring purposes. We quantified proportional daily captures per unit effort by species over the trapping period separately for 2014, 2015, and 2016. We used these proportions to calculate averages using a 5-d moving window, excluding days not trapped

Table 4
Average of the annual occupancy estimates (ψ) and associated standard error (SE) for 9 species of small mammals captured in 2014, 2015, and 2016 on San Antonio Viejo and El Sauz lands in southern Texas, United States, using 3, 4, 5, and all 6 d of trapping data.

Species	Days of trapping							
	3		4		5		6	
	ψ	SE	ψ	SE	ψ	SE	ψ	SE
Northern pygmy mouse	0.21	0.07	0.23	0.07	0.24	0.07	0.25	0.07
Pocket mice	0.69	0.07	0.71	0.07	0.75	0.06	0.79	0.05
Kangaroo rats	0.35	0.09	0.38	0.09	0.40	0.08	0.40	0.08
Southern Plains woodrat	0.53	0.09	0.56	0.09	0.59	0.09	0.61	0.09
Northern grasshopper mouse	0.67	0.07	0.68	0.07	0.68	0.07	0.68	0.07
White-footed mouse	0.81	0.06	0.82	0.06	0.83	0.06	0.84	0.06
Merriam's pocket mouse	0.53	0.12	0.63	0.10	0.62	0.09	0.61	0.09
Fulvous harvest mouse	0.29	0.08	0.30	0.08	0.37	0.08	0.40	0.08
Hispid cotton rat	0.26	0.06	0.28	0.07	0.29	0.07	0.31	0.07

because of inclement weather. Seasonal weather in southern Texas is highly variable and likely translates to shifts in annual patterns in animal activity. We accounted for annual variation by averaging the 5-d moving windows across all 3 yr of records.

Our calculations for seasonal animal activity indicate high variability with seasonal patterns for some species (Fig. 3). Approximately half of all captures of hispid cotton rats (*Sigmodon hispidus*) occurred during a 10-d period centered on the third week of February (Fig. 3C). Approximately 35% of all captures of fulvous harvest mice also occurred in this period of February. There were only three captures of hispid cotton rats before d 40 and a single capture of a northern pygmy mouse before d 45. Other species, such as kangaroo rats and Southern Plains woodrats, appeared to have multiple peaks in activity that were spaced throughout the trapping period (Fig. 3A).

Step 4. Conduct Power Analyses

Conducting a power analysis for detecting trends requires multiple steps that involve simulating population trajectories according to the effect size and time periods outlined in step 2 with estimates of the monitoring metric generated in step 3 as the starting values (Fig. 1D). Typically, thousands of trajectories are simulated using the variance associated with the metric estimate to simulate sampling variance (Gibbs, 2000). Some test is then performed to determine if there is significant evidence for a trend line with a slope not equal to 0 for each simulation. Further simulations can then be made by manipulating effort, such as number of areas sampled, and assuming some relationship between sample size and the precision of resulting estimates. Power is then calculated as a proportion of each simulated dataset under a specific scenario of effect size, time period, and effort for which a slope not equal to 0 was identified. Since metric estimates and variance generally vary among species, it will likely be informative for developing monitoring scenarios to conduct separate power analyses for at least a representative subset of species that are under consideration for inclusion in the proposed monitoring program.

We ran a comprehensive power analysis for the white-footed mouse, which was both abundant (average $\hat{N} = 31.8$, SE = 11.1) and common (estimated $\psi = 0.82$, SE = 0.058); hispid cotton rat, which was abundant (average $\hat{N} = 29.5$, SE = 2.2) but uncommon (estimated $\psi = 0.28$, SE = 0.066); and fulvous harvest mouse, which had low abundance (average $\hat{N} = 11.6$, SE = 5.6) and was uncommon (estimated $\psi = 0.31$, SE = 0.075; Appendix A). We used the SE associated

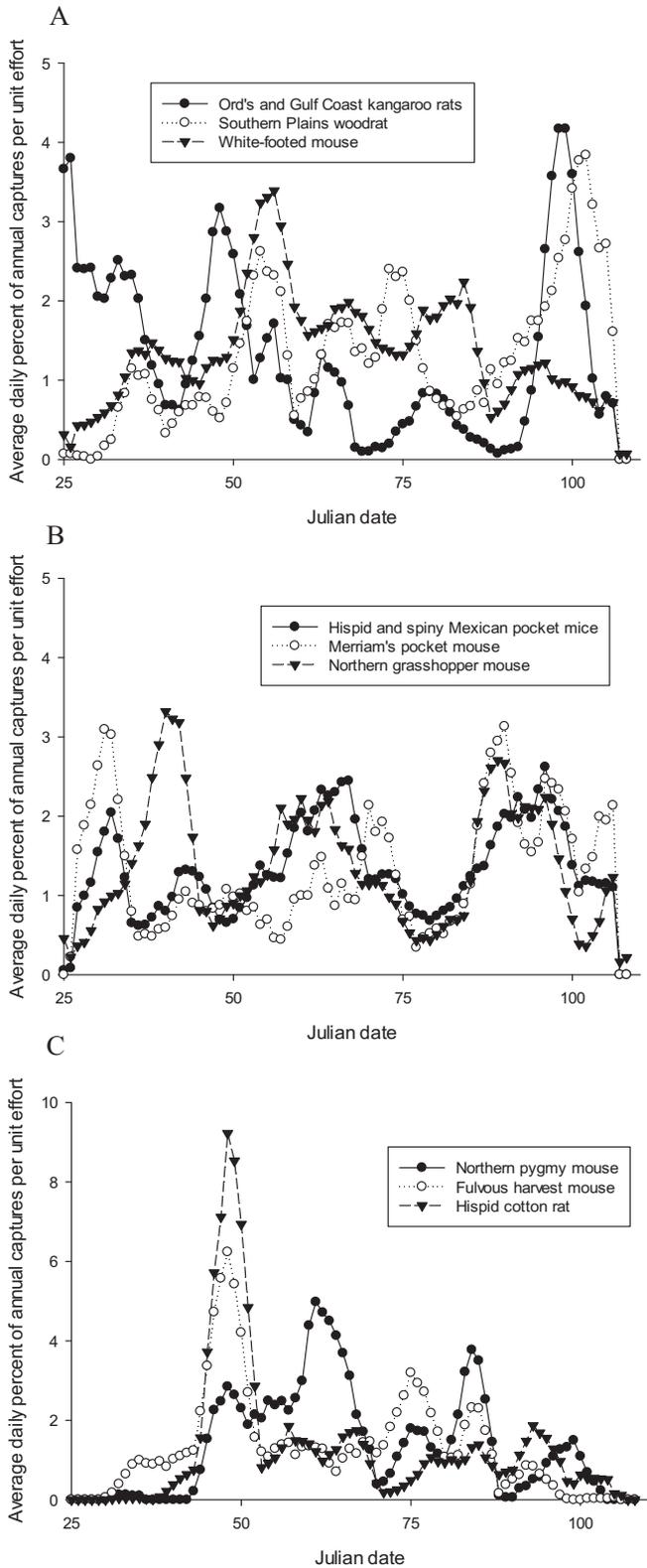


Figure 3. Running 5-d average daily percent of total annual captures per unit effort, averaged across all 3 yr of trapping for each species captured on the East Foundation's San Antonio Viejo and El Sauz Ranches, Texas, United States, 2014–2016.

with each parameter estimate to simulate sampling variance and assumed a constant CV over the projected decline. Our power analyses suggested that detecting an annual change in abundance of < 10% at a power of 0.90 for the white-footed mouse would not be possible with

≤ 50 grids, even over a 10-yr duration (Fig. A.1). Our data showed that a 20% annual change would be detected with a power of 0.90 with 25 grids after 10 yr (Fig. A.2). This effect size represented projected abundances after 10 yr of either 4 animals for a negative growth or 164 animals for a positive growth, with a beginning population size of 32 individuals (Table A.1).

Due to the low CV associated with hispid cotton rat abundance estimates (0.17), we predicted small effect sizes detectable with fewer trapping grids than for other species. Our simulations suggested that 15 grids would provide power of 0.90 to detect annual changes in abundance of 11% after 3 yr, 5% after 5 yr, and 2% after 10 yr (Fig. A.3). We predicted a 10% annual change after 3 yr would be detected with a power of 0.90 with 15 grids, a 5% annual change after 5 yr would be detected with a power of 0.90 with 20 grids, and a 1% annual change after 10 yr with a power of 0.90 with 40 grids (Fig. A.4).

Our power analysis suggested it should be possible to detect a 10% annual change in abundance after 10 yr for fulvous harvest mice with a power of 0.90 with 50 grids (Fig. A.5). We also estimated it was possible to detect a 20% annual change in abundance after 10 yr with power of 0.90 with around 20 grids (Fig. A.6). This effect size represented projected abundances after 10 yr of either 2 animals for a negative growth, or 60 animals for a positive growth, with a beginning population size of 17 individuals (Table A.3).

With a 50% net decline in proportion of sites occupied by white-footed mice occurring over 3 yr, we predicted the change would be detected with power of 0.90 with sampling 30 sites each yr (Fig. A.7). A similar net reduction occurring over 5 yr should be detectable with 23 grids, and over 10 yr it should be detectable with as few as 15 grids. We predicted a net change of 25% over 10 yr would be detected at power of 0.90 with approximately 48 sampling sites (Fig. A.8).

Effect sizes for changes in occupancy rates with power of 0.90 for hispid cotton rats were large (poor) but improved with 45 or more sites sampled (Fig. A.9). We predicted that with a power of 0.90, 45 sites would allow for detecting a net change in occupancy of 65% over 10 yr, 75% over 5 yr, and 85% over 3 yr (Fig. A.10).

Our power analysis for fulvous harvest mouse occupancy suggested substantial improvements in effect size detected with power of 0.90 by increasing sample sizes above 45 sites sampled (Fig. A.11). We predicted that with a power of 0.90, between 30 and 35 sites would allow for the detection of a net change of 65% over 10 yr, a net change of 75% over 5 yr, and a net change of 85% over 3 yr (Fig. A.12).

Step 5. Develop Monitoring Scenarios

If all objectives and level of sensitivity were identified a priori, a single monitoring scenario may be developed from the power analysis that most effectively meets the stated objectives based on some criteria, such as cost. In situations where these decisions have not been made, it is useful to develop multiple, alternative monitoring scenarios based on a range of reasonable targets or required effort (Fig. 1E). Once the alternative scenarios are defined, the resulting level of sensitivity will need to be calculated for each species included. Finally, costs to implement each alternative scenario must be estimated so that tradeoffs of sensitivity and costs can be compared.

In our example, we did not have a stated effect size and we considered three separate durations. Thus, we considered a range of values as alternative monitoring scenarios. In addition, since we included two potential monitoring metrics, we identified separate scenarios specific to each metric. We used the results from our power analysis that we conducted on a subset of species to develop four distinct monitoring scenarios. We then ran power analyses for the remaining species for the level of effort specified by each scenario to determine the resulting species-specific level of sensitivity. Because our objectives were to develop a monitoring program for multiple species and it is unreasonable to expect all species to occupy each sampling location, we corrected the sample sizes in our recommendations for monitoring abundance with

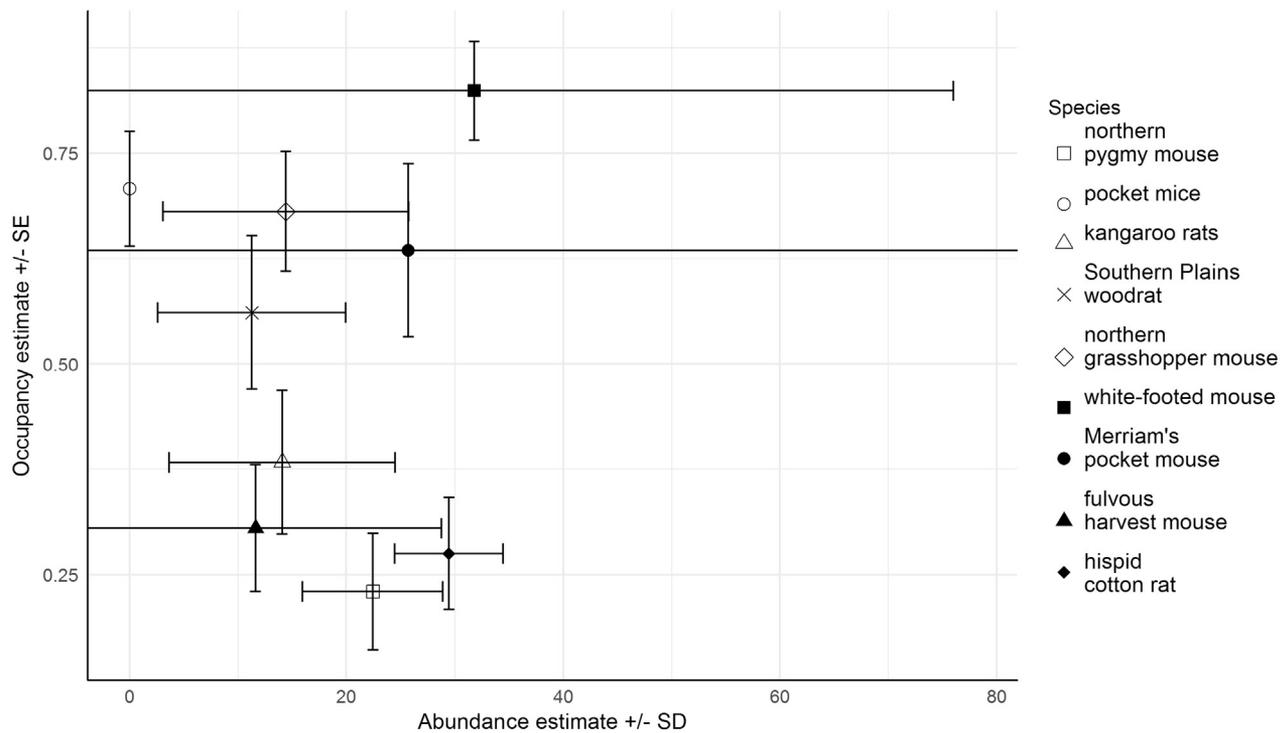


Figure 4. Estimates and variance for abundance from 6 d of trapping and occupancy from 4 d of trapping for species captured on the East Foundation's San Antonio and El Sauz Ranches in southern Texas, United States, 2014–2016. We were unable to generate a useful estimate of abundance for the pocket mice complex. Note that our abundance estimates - the SE for white-footed mouse (-12.4), Merriam's pocket mouse (-74.4), and fulvous harvest mouse (-5.6) extend below 0, and our abundance estimate + SE for Merriam's pocket mouse (125.7) extends beyond the scale displayed.

the occupancy rate we estimated for each species. For instance, using a monitoring scenario with 50 sampling sites each yr, if a particular species had an estimated occupancy of 0.50, we would base our estimate of effect size on an effective sample size of 25 sites.

We developed 4 monitoring scenarios and estimated power and associated costs for each. Two of these scenarios involved monitoring both abundance and occupancy, so they were based on trapping 6 consecutive d using trapping grids. The other two involved only monitoring occupancy, so they were based on trapping for 4 consecutive d using transects.

From our analysis of the patterns of captures we observed in our 3 yr of data, we recommend the planned duration of trapping in our study area in southern Texas be centered around Julian date 75 (mid-March). In addition, we recommend a small mammal trapping season not begin before Julian date 45 (mid-February), as it appears that northern pygmy mouse and hispid cotton rat captures are low before this date. We also recommend trapping end before Julian date 105 (mid-April), as our sampling beyond this date was insufficient to allow for prediction of capture rates. From our efforts to refine field methods to optimize the tradeoff between area of coverage and effort, we recommend using square grids of 121 stations with 20 m spacing

and rectangular transects with an arrangement of 3×19 trap stations with 25-m spacing for monitoring small mammals on our study area.

Scenario A: Maximize Number of Species for Detecting a 10% Annual Change in Abundance After 10 Yr

We developed scenario A to maximize the number of species for which a biologically meaningful change in abundance could be detected after 10 yr with what we considered to be a reasonable level of effort. Scenario A required the use of 40 square trapping grids trapped for 6 consecutive d. We estimated with scenario A that it should be possible to detect annual changes in abundance of $\leq 10\%$ after 10 yr for four species (Table 6; hispid cotton rat, northern pygmy mouse, Southern Plains woodrat, and northern grasshopper mouse). With this same effort, we estimated that it will also be possible to detect net declines in occupancy rates of $< 50\%$ after 10 yr for five species (Table 7; white-footed mouse, pocket mice, northern grasshopper mouse, Southern Plains woodrat, and Merriam's pocket mouse). The estimated annual labor costs for scenario A were \$72 462 (see Table 5).

Table 5
Labor cost estimates for trapping a single transect for 4 nights, a single grid for 6 nights, and costs estimates for Scenarios A–D developed for long-term monitoring the small mammal assemblage on East Foundation lands in southern Texas, United States. Setup is the estimated time to locate each trap station at a site and place traps. Our recommendations are to keep traps closed during the day to reduce trap mortality; therefore, we estimate the time to check traps in the morning and open them each evening. Travel time includes daily trips to check and open traps and a single trip to set up sites. Total costs are based on costs to employ technicians during the 2016 field season (\$3 100/mo, or \$19.375/hr).

Trapping strategy	Time (hr)						Total cost	Scenario			
	Set up	Check	Open in evening	Data entry	Travel	Total hours		A	B	C	D
Transect (4 d)	5.25	8.25	2	1	33.75	50.25	\$974			60	30
Grid (6 d)	12.25	23	6	3.5	48.75	93.5	\$1,812	40	20	\$58 416	\$29 208

Scenario B: Monitor a Selected Subset of Species for Detecting a 25% Annual Change in Abundance After 10 Yr

We designed scenario B to allow for monitoring abundance with less sensitivity than with scenario A and therefore require less effort. Scenario B involved trapping 20 square grids for 6 consecutive d. Under scenario B, we estimated that it should be possible to detect annual changes in abundance < 10% for two species (hispid cotton rat and northern pygmy mouse) and ≤ 15% for two additional species (Southern Plains woodrat and northern grasshopper mouse) with 10 yr of trapping (Table 8). This effort should also allow detection of declines in net occupancy rate < 50% for two species (white-footed mouse and pocket mice) and at ≤ 60% for an additional three species (northern grasshopper mouse, Southern Plains woodrat, and Merriam's pocket mouse) after 10 yr (Table 9). The estimated annual labor costs for scenario B were \$36 231 (see Table 5).

Scenario C: Monitor Occupancy Only, with Greater Sensitivity but Less Cost Than with Scenario A

We designed scenario C based on the objective of monitoring occupancy only. As such, scenario C used 60 transects trapped for 4 consecutive d. With this effort, it should be possible to detect net declines in occupancy after 10 yr between 25% and 35% for three species (white-footed mouse, pocket mice, and northern grasshopper mouse), between 40% and 50% for another three species (Southern Plains woodrat, Merriam's pocket mouse, and kangaroo rats), and between 60% and 70% for the final three species (Table 10; fulvous harvest mouse, hispid cotton-rat, and northern pygmy mouse). The estimated annual labor costs for scenario C were \$58 415 (see Table 5).

Scenario D: Monitor Occupancy Only, with Greater Sensitivity, but Less Cost Than with Scenario B

We designed scenario D based on monitoring only occupancy with a substantial reduction in costs from Scenario C. The effort for scenario D included trapping 30 transects for 4 consecutive d. This effort should allow power to detect annual changes in occupancy rates after 10 yr between 35% and 55% for five species (white-footed mouse, pocket mice, northern grasshopper mouse, Southern Plains woodrat, and Merriam's pocket mouse) and between 70% and 85% for the remaining 4 species (Table 11; kangaroo rats, Fulvous harvest mouse, hispid cotton-rat, and northern pygmy mouse). The estimated annual labor costs for scenario D were \$29 207 (see Table 5).

Table 6

Sensitivity estimates for monitoring abundance of small mammals under Scenario A for the East Foundation, southern Texas, United States. We developed Scenario A to maximize number of species for which a 10% change in abundance could be detected after 10 yr with power of 0.90 and involves trapping 6 consecutive nights with 40 square grids. The first 2 columns are the values for population size (\hat{N}) and standard deviation (SD) we used for the power simulations. Effective sampling size (n_e) was calculated by multiplying the proposed number of sampling locations (40) by each species's estimated occupancy rate. Remaining columns are the smallest negative (–) and positive (+) annual and net percent change in abundance we estimate should be detectable after 5 and 10 yr of sampling, as well as the projected, respective population size for each species. Blanks indicate annual change of < 50% could not be reached with the effective sample size.

Species	\hat{N}	SD	n_e	5-yr effect size						10-yr effect size					
				% change				Projected \hat{N}		% change				Projected \hat{N}	
				annual	net	–	+	–	+	annual	net	–	+	–	+
Hispid cotton rat	29.5	5.02	13	–6	6	–21.9	26.2	23.0	37.2	–2	2	–16.6	19.5	24.6	35.2
Northern pygmy mouse	22.4	6.48	10	–12	12	–40.0	57.4	13.5	35.3	–4	4	–30.7	42.3	15.5	31.9
Northern grasshopper mouse	14.4	11.33	27	–24	29	–66.6	176.9	4.8	39.9	–9	10	–57.2	135.8	6.2	34.0
Southern Plains woodrat	11.3	8.67	24	–24	30	–66.6	185.6	3.8	32.2	–9	10	–57.2	135.8	4.8	26.5
Kangaroo rats	14.1	10.41	16	–30	36	–76.0	242.1	3.4	48.1	–11	13	–65.0	200.4	4.9	42.2
White-footed mouse	31.8	44.19	33	–38		–85.2		4.7		–14	17	–74.3	310.8	8.2	130.6
Fulvous harvest mouse	11.6	17.17	16	–48		–92.7		0.8		–17	24	–81.3	593.1	2.2	80.4
Merriam's pocket mouse	25.7	100.07	25							–23	38	–90.5	1 715.1	2.4	466.6

Table 7

Sensitivity estimates for monitoring occupancy of small mammals under Scenario A for the East Foundation, southern Texas, United States. We developed Scenario A to maximize number of species for which a 10% change in abundance could be detected after 10 yr with power of 0.90 and involves trapping 6 consecutive nights with 40 square grids. The first 2 columns are the values for occupancy (Ψ -hat) and standard error (SE) we used for the power simulations. The remaining columns are the smallest negative net percent change in occupancy we estimate should be detectable after 5 and 10 yr of sampling and the projected, respective occupancy rate for each species.

Species	Ψ -hat	SE	5-yr effect size		10-yr effect size	
			Net % decline	Projected ψ	Net % decline	Projected ψ
White-footed mouse	0.84	0.06	35	0.54	30	0.59
Pocket mice	0.79	0.05	40	0.47	35	0.51
Northern grasshopper mouse	0.68	0.07	50	0.34	40	0.41
Southern plains woodrat	0.61	0.09	55	0.27	45	0.33
Merriam's pocket mouse	0.61	0.09	60	0.25	45	0.34
Kangaroo rats	0.40	0.08	75	0.10	60	0.16
Fulvous harvest mouse	0.40	0.08	75	0.10	60	0.16
Hispid cotton rat	0.31	0.07	80	0.06	70	0.09
Northern pygmy mouse	0.25	0.07	90	0.02	75	0.06

Step 6. Initiate Program

Select a Monitoring Scenario

Once all the proposed alternative monitoring scenarios are developed and the operating costs for each scenario have been presented, the tradeoffs between level of sensitivity and operating costs can be evaluated. This type of comparison allows for the consideration of opportunity costs where a specific decrease in costs between two scenarios is associated with a specific loss in sensitivity and potential information. Once identified, the most appropriate scenario should then be implemented, thus beginning the long-term dataset.

Reassess Power with Additional Data

The scenarios and associated effect sizes presented earlier are based on statistical power that we estimated from preliminary data we collected over 3 yr of sampling. Although these estimates are statistically unbiased, we recognize that they are based on simple models that were fit to limited data. Our understanding of complex natural systems may only be improved on with additional data. It is therefore critical that, regardless of the scenario used for long-term monitoring, results

Table 8
Sensitivity estimates for monitoring abundance of small mammals under Scenario B for the East Foundation, southern Texas, United States. We developed Scenario B to detect a 25% change in abundance after 10 yr with power of 0.90 for a subset of species, which involves trapping 6 consecutive nights with 20 square grids. The first 2 columns are the values for population size (N) and standard deviation (SD) we used for the power simulations. Effective sampling size (n_e) was calculated by multiplying the proposed number of sampling locations (20) by each species's estimated occupancy rate. Remaining columns are the smallest negative (–) and positive (+) annual and net percent change in abundance we estimate should be detectable after 5 and 10 yr of sampling, as well as the projected, respective population size for each species. Blanks indicate annual change of < 50% could not be reached with the effective sample size.

Species	N	SD	n_e	5-yr effect size						10-yr effect size							
				% change				Projected \hat{N}		% change				Projected \hat{N}			
				annual		net		–	+	–	+	annual		net		–	+
				–	+	–	+					–	+	–	+		
Hispid cotton rat	29.5	5.02	6	–8	8	–28.4	36.0	21.1	40.1	–3	3	–24.0	30.5	22.4	38.4		
Northern pygmy mouse	22.4	6.48	5	–16	17	–50.2	87.4	11.2	42.0	–6	6	–42.7	68.9	12.9	37.9		
Southern plains woodrat	11.3	8.67	12	–34	46	–81.0	354.4	2.1	51.2	–12	14	–68.4	225.2	3.6	36.6		
Northern grasshopper mouse	14.4	11.33	14	–35	44	–82.1	330.0	2.6	61.9	–12	15	–68.4	251.8	4.6	50.7		
Kangaroo rats	14.1	10.41	8	–42		–88.7		1.6		–15	19	–76.8	378.5	3.3	67.3		
Fulvous harvest mouse	11.6	17.17	8							–23	38	–90.5	1715.1	1.1	210.5		
White-footed mouse	31.8	44.19	17							–19	26	–85.0	700.5	4.8	254.5		
Merriam's pocket mouse	25.7	100.07	12							–32	N/A	–96.9		0.8			

be regularly analyzed to ensure the minimum desired power is being reached. We recommend that statistical power be reassessed after each field season of data collection, and methods and sample sizes should be adjusted as needed (Field et al., 2007; Fig. 1F –feedback loop). It is important to note that our estimates of detectable effect size for monitoring abundance are based on estimates of proportion of sites occupied. For example, our estimate for detectable effect size for monitoring hispid cotton rat under scenario A (see Table 6) is based on our estimate that 13 of the 40 sampled sites will be occupied by the species. If the actual occupancy rate drops, the effort of 40 sites may no longer provide the power we estimate with this scenario. In addition, as populations decline, resulting sample sizes will decline, potentially diminishing precision to the point that estimates are of no use and possibly leading to the situation where models cannot be fit to the data using the specified framework. Monitoring objectives that include the ability to detect declines in abundance or occupancy of species that already have low abundance or are uncommon may require additional consideration. It may be more appropriate to simulate data that would be collected during a decline and attempt to fit models to these data to more accurately assess power and determine required sample sizes in these situations.

Table 9
Sensitivity estimates for monitoring occupancy of small mammals under Scenario B for the East Foundation, southern Texas, United States. We developed Scenario B to detect a 25% change in abundance after 10 yr with power of 0.90 for a subset of species, which involves trapping 6 consecutive nights with 20 square grids. The first 2 columns are the values for occupancy (Ψ -hat) and standard error (SE) we used for the power simulations. The remaining columns are the smallest negative net percent change in occupancy we estimate should be detectable after 5 and 10 yr of sampling and the projected, respective occupancy rate for each species.

Species	Ψ -hat	SE	5-yr effect size		10-yr effect size	
			Net % decline	Projected ψ	Net % decline	Projected ψ
White-footed mouse	0.84	0.06	55	0.38	40	0.50
Pocket mice	0.79	0.05	55	0.35	45	0.43
Northern grasshopper mouse	0.68	0.07	65	0.24	55	0.31
Southern plains woodrat	0.61	0.09	75	0.15	60	0.24
Merriam's pocket mouse	0.61	0.09	75	0.15	60	0.25
Kangaroo rats	0.40	0.08	90	0.04	80	0.08
Fulvous harvest mouse	0.40	0.08	90	0.04	80	0.08
Hispid cotton rat	0.31	0.07	95	0.02	90	0.03
Northern pygmy mouse	0.25	0.07	NA	NA	95	0.01

Discussion

We developed four options for long-term monitoring of a small mammal assemblage on lands in southern Texas in our example. Our monitoring scenarios included two metrics and a range of required effort that was reflected in the respective effect sizes. Although our results were specific to our study area, our study should provide a useful framework for others to follow for developing long-term monitoring programs according to their specific needs.

Selecting sampling sites based on vegetation strata may improve precision of estimated metrics and hence power of the monitoring program if a substantial amount of variation in the metric occurs among strata and metrics are estimated separately for each stratum (Scheaffer et al., 2006). We selected sites for our initial study using a stratified random sampling design in which we used primary vegetation types as our strata and attempted to allocate effort equally among the most common vegetation types. Our restriction of a minimum of two sampling sites per stratum potentially resulted in slightly more variation in our data than what we would expect from a completely random sample; thus, our power estimates may be somewhat low. Our reasoning was to ensure that we captured the majority of variation in species

Table 10
Sensitivity estimates for monitoring occupancy of small mammals under Scenario C for the East Foundation, southern Texas, United States. We developed Scenario C to monitor occupancy only, with greater sensitivity but less cost than with Scenario A. Scenario C requires trapping 4 consecutive nights with 60 transects. The first 2 columns are the values for occupancy (Ψ -hat) and standard error (SE) we used for the power simulations. The remaining columns are the smallest negative net percent change in occupancy we estimate should be detectable after 5 and 10 yr of sampling, and the projected, respective occupancy rate for each species.

Species	Ψ -hat	SE	5-yr effect size		10-yr effect size	
			Net % decline	Projected ψ	Net % decline	Projected ψ
White-footed mouse	0.82	0.06	30	0.58	25	0.62
Pocket mice	0.71	0.07	40	0.43	30	0.50
Northern grasshopper mouse	0.68	0.07	40	0.41	35	0.44
Southern plains woodrat	0.56	0.09	50	0.28	40	0.34
Merriam's pocket mouse	0.63	0.10	50	0.32	40	0.38
Kangaroo rats	0.38	0.09	65	0.13	50	0.19
Fulvous harvest mouse	0.30	0.08	75	0.08	60	0.12
Hispid cotton rat	0.28	0.07	75	0.07	60	0.11
Northern pygmy mouse	0.23	0.07	80	0.05	70	0.07

Table 11

Sensitivity estimates for monitoring occupancy of small mammals under Scenario D for the East Foundation, southern Texas, United States. We developed Scenario D to monitor occupancy only, with greater sensitivity but less cost than with Scenario B. Scenario D requires trapping 4 consecutive nights with 30 transects. The first 2 columns are the values for occupancy (Ψ -hat) and standard error (SE) we used for the power simulations. The remaining columns are the smallest negative net percent change in occupancy we estimate should be detectable after 5 and 10 yr of sampling and the projected, respective occupancy rate for each species.

Species	Ψ -hat	SE	5-yr effect size		10-yr effect size	
			Net % decline	Projected ψ	Net % decline	Projected ψ
White-footed mouse	0.82	0.06	45	0.45	35	0.54
Pocket mice	0.71	0.07	50	0.35	45	0.39
Northern grasshopper mouse	0.68	0.07	55	0.31	45	0.37
Southern plains woodrat	0.56	0.09	65	0.20	55	0.25
Merriam's pocket mouse	0.63	0.10	65	0.22	55	0.29
Kangaroo rats	0.38	0.09	85	0.06	70	0.11
Fulvous harvest mouse	0.30	0.08	90	0.03	80	0.06
Hispid cotton rat	0.28	0.07	90	0.03	80	0.06
Northern pygmy mouse	0.23	0.07	NA	NA	85	0.03

associated with the various vegetation types. We would not recommend that long-term sampling stations be selected in this way as vegetation types are likely to change over the duration of the monitoring program via succession, management, or otherwise. We recommend selecting a probabilistic sample for permanent sampling sites, and if stratification is used, soil type or similar descriptor that is less prone to change is used for the strata (Johnson, 2012). Further, doing so may improve power or reduce sample size required to detect a specific effect size.

It is critical that the same monitoring protocol employed to estimate power be used for the actual monitoring program for power estimates to remain valid. In our example, this would require the application of the same type of bait, ratio of trap types, and placement of traps 3 d before trapping that we used in the current study. Similarly, our power calculations were based on parameter estimates generated from data collected over 3 yr where we made slight modifications to the trap configurations to both the grids and transects. Thus, we expect our sensitivity estimates would only be accurate for monitoring scenarios using an effort (density of traps, area trapped, and length of transect) similar to the average of what we used. By considering the within-season patterns of captures for each species in our example, we were able to make recommendations regarding the timing of sampling to maximize capture and detection probabilities. Following our recommendations on timing of sampling should increase the probability that the power of the monitoring program is at least as high as we predicted. The effect on power of any deviations from the protocol used to develop proposed monitoring scenarios would need to be assessed before implementing. Otherwise, managers risk wasting resources and collecting data that are inadequate for decisions and planning objectives.

Our recommendations for monitoring the system in our example include collecting data annually. In certain systems, collecting data on alternating years may be desirable for detecting change, particularly where trends are strictly linear and annual variation is small. However, due to the highly variable nature of the weather in southern Texas, skipping years of sampling would likely decrease power to detect trends, particularly nonlinear ones, and offset any cost savings (Guillera-Aroita and Lahoz-Monfort, 2012). Sampling less than annually would also result in a greater potential to miss critical events, such as impacts of wildfires or severe weather events. Furthermore, power to detect trends of given magnitudes under a scenario of sampling at intervals less than annually are potentially different from those that we derived from annual sampling (Gerrodette, 1987). If less frequent than annual monitoring is to be considered as a potential scenario, the power analysis used to determine effect size would need to be modified specifically

to reflect the actual sampling frequency relative to projected population changes.

In our study, we sought to develop a monitoring program based on our best estimates of statistical power with the expectation that power would be reassessed on a regular basis. With additional data, new estimates would be generated and effort would be adjusted as needed to minimize loss of information from the long-term dataset that may have resulted from initial estimates of power that were biased high. For those developing monitoring programs where insufficient information from a single year is not acceptable, or where power will not be frequently reassessed, we recommend taking a more conservative approach. Specifically, we suggest using the bounds of the confidence intervals based on an appropriate alpha, rather than actual point estimates as we have done. For instance, we suggest using the lower confidence bound of initial abundance and occupancy estimates for determining power, and for the estimate of occupancy to select a sample size that would result in an effective sample size desired for estimating abundance.

Our estimates for costs associated with each of the scenarios we present are strictly for field efforts and do not include costs for initial purchase and maintenance of all required equipment. We also excluded costs for bait and bedding, which we determined to be insignificant relative to other costs. Finally, we do not include estimates of costs for regular analyses of data collected as part of the long-term monitoring program; however, we strongly recommend this effort be considered and adequately budgeted for. Failure to do so may jeopardize reaching the long-term objectives, even for properly designed monitoring programs.

Our study serves as an example of how to develop a rigorous monitoring program for rangeland fauna. We presented multiple scenarios for application to rangelands because there is no optimal metric for detecting change in abundance or occupancy per se; each individual or group responsible for making management decisions must determine the level of change that needs to be identified over a given period of time. It should be clear, however, that developing a long-term monitoring program with proper estimates of power and sensitivity requires preliminary data. In the absence of relevant preliminary data, an initial (3 yr in our case) period of intensive sampling is necessary to generate estimates of power for proposed sampling methods and sampling intensities. These estimates allow for the development of alternative monitoring scenarios such that opportunity costs can be evaluated. Although there is no single best solution, our study design, analyses, and results serve as a reasonable framework that can be used as a starting point for other such efforts regardless of the species considered for monitoring or the type of terrestrial vegetation occupied.

While we include specific recommendations for monitoring the small mammal assemblage on the East Foundation, such as sample sizes and timing, we discourage using our monitoring scenarios elsewhere with the expectation that sensitivity would be the same as we predict from our study. It should be clear that our estimates were based on data collected on our study sites. Therefore, our recommendations are not valid elsewhere without further testing with an appropriate dataset.

Implications

The steps that we outlined earlier should provide a general guideline for land managers or landowners with conservation goals for developing a long-term monitoring program specific to their objectives (see Fig. 1). Once target species and monitoring metrics are selected, it is critical to generate estimates of power for specific levels of effort, effect sizes, duration, and significance. It may be possible to estimate power from prior data; however, unless these data were collected in the same location with the same methods proposed for the monitoring, we strongly suggest initial sampling be implemented to generate these estimates directly as we did. The estimates of effect size and

power then become the foundation from which monitoring scenarios can be developed. Developing multiple scenarios, each with their specific operating cost, presents the additional benefit of allowing for the consideration of the various tradeoffs between effort and sensitivity among competing scenarios.

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Appendix A. Supplementary data

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