

Statistical power of mobile acoustic monitoring to detect population change in southeastern U.S. bat species, a case study

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ABSTRACT

Bat populations in eastern North America have experienced precipitous declines following the spread of white-nose syndrome (WNS) and other population stressors. It is imperative to understand changes in bat populations as WNS spreads to provide appropriate guidance for species management. We developed generalized linear mixed-models of population trend and habitat associations for five indicator bat species on U.S. Fish and Wildlife Service Mobile Acoustic Bat Monitoring program routes across 86 sites in the southeastern United States from 2012 to 2017. We estimated substantial declining annual trends in relative abundance of tricolored bat (*Perimyotis subflavus*; -15.1% [-20.6 to -9.1% 95% CI]) and little brown bat (*Myotis lucifugus*; -13.9% [-22.9 to -3.8% 95% CI]). Relative abundance of bat species increased throughout the summer, and associated positively with the amount of woody cover along survey routes in all but *P. subflavus*. Fewer evening bats (*Nycticeius humeralis*) and eastern red bats (*Lasiurus borealis*) were detected along more developed routes. Using these models, we conducted a prospective power analysis to examine sampling effort necessary to detect moderate to catastrophic population changes in bat populations. We estimated that it would require 10–20 years of surveys on 50–100 routes to detect 5% annual declines in all species at 80% power and $\alpha = 0.1$. Detecting a 2.73% annual decline may require >200 surveys over >20 years; whereas a 1.14% annual decline was nearly impossible to detect via our program. We demonstrate and caution that underpowered monitoring programs may misrepresent the magnitude and/or sign of population trajectories. We recommend project-specific power analysis continue to be emphasized as an important study design component for effective long-term monitoring programs.

1. Introduction

Bat populations in eastern North America have experienced precipitous, catastrophic declines in the last decade following the emergence and spread of the fungal disease *Pseudogymnoascus destructans* (*Pd*), which causes white-nose syndrome (WNS) in hibernating bats as well as other factors (Frick et al., 2020; Ingersoll et al., 2013; O'Shea et al., 2016). We now know the spread of WNS reduced bat population by as much as 6 million individuals across 20 or more species in eastern North America (U.S. Fish and Wildlife Service, 2019). However, other threats related to habitat change or loss, energy development, and environmental contaminants likely exert detrimental influences on North American bat populations as well (Frick et al., 2020; O'Shea et al.,

2016). Effective monitoring programs that evaluate changes in populations typically require significant time and fiscal resources. Monitoring programs designed to track population change and infer ecological significance must therefore take measures to minimize bias, and when possible optimize allocation of survey effort to allow for reliable and robust statistical inference within the constraints of available resources for implementation (D'Acunto et al., 2018; Field et al., 2005).

Bats present multiple monitoring challenges due to their aerial foraging habits, variable spatiotemporal activity patterns, and difficulty of/in discriminating individuals and species when surveyed non-invasively (Barlow et al., 2015; de Torrez et al., 2017; O'Shea et al., 2003; Whitby et al., 2014). Notwithstanding the challenges, the bat

Abbreviations: WNS, White-nose syndrome; MABM, Mobile Acoustical Bat Monitoring.

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conservation community acknowledges the need to improve understanding of bat populations through standardized and robust monitoring strategies that minimize and account for these sources of variation (O'Shea et al., 2003). Since the early to mid-2000's, monitoring programs have been implemented to track regional bat population trends around the world (e.g., Barlow et al., 2015; Battersby, 2010; Jones et al., 2013; Roche et al., 2011; Rodhouse et al., 2012). The majority of these deploy stationary or acoustic monitoring strategies to assess changes in call counts as an index for population change over time. Prospective power analysis can play an important role in the design of long-term monitoring programs to help estimate the minimum amount and frequency of sampling effort necessary to detect a specified trend with a desired level of precision under a specific type I error rate and power, assuming the modeling framework is reasonable (Magurran et al., 2010). Understanding power of monitoring programs to estimate changes to bat populations is particularly important in the face of expected abrupt population declines from WNS spread, in addition to detecting gradual population declines from less precipitous threats. A failure to detect population trajectories, or to mischaracterize their severity, due to limited statistical power may translate into grievous errors in population management (Gibbs et al., 1998). Several regional and national bat monitoring programs have thus successfully implemented power analyses to estimate their ability to detect moderate to substantial population changes (Banner et al., 2019; Barlow et al., 2015; International Union for Conservation of Nature, 2012; O'Donnell and Langton, 2003; Roche et al., 2011).

The U.S. Fish and Wildlife Service (FWS) National Wildlife Refuge System initiated a Mobile Acoustic Bat Monitoring (MABM) program in 2012 to track long-term bat population trends across National Wildlife Refuges in the Southeast and Midwest in anticipation of WNS spread across the U.S. (U.S. Fish and Wildlife Service, 2012). The MABM program includes vehicle-based road transects conducted each summer on participating field stations, and provides the first comprehensive baseline inventory of bat species occurrence on National Wildlife Refuges in the region (U.S. Fish and Wildlife Service, 2012). In this study, we analyzed MABM data to estimate population trends and habitat associations for a suite of bat species vulnerable to declines caused by WNS or other population stressors on National Wildlife Refuges and other FWS field stations. We used the resulting model parameter estimates to inform a prospective power analysis for five widespread bat species/species groups to evaluate the sampling effort needed to reliably detect various levels of population declines. We discuss how similar assessments (within the context of a given monitoring program) could be used to recommend strategies for long-term acoustic monitoring of bats in the eastern U.S. and in other regions.

2. Materials and methods

2.1. Survey methods

The MABM program includes 86 survey routes at 63 FWS field stations (61 National Wildlife Refuges, 2 Ecological Services Field Offices) in 14 southeastern and midwestern states (Fig. 1). Sites were selected based on voluntary participation, but targeted field stations without presumed population impacts from WNS in 2011 but at risk for WNS as the disease spreads westward. We worked with FWS staff to design and implement mobile vehicular survey routes following recommendations in Britzke and Herzog (2009). Survey routes (33.3 ± 15.1 km [SD] in length [range 1.5 to 62.4 km]) were established on navigable, low-traffic-volume secondary and tertiary roads, and were designed intentionally to intersect the range of representative ecosystem types on the field station while maintaining safety of surveyors (U.S. Fish and Wildlife Service, 2012). Forested roadways comprised much of the sampled area, but routes commonly included wetlands, lakes and moist-soil units, reforestation areas (pine and hardwood), agricultural planted fields, and fallow fields (Fig. S1). Open water and developed land cover

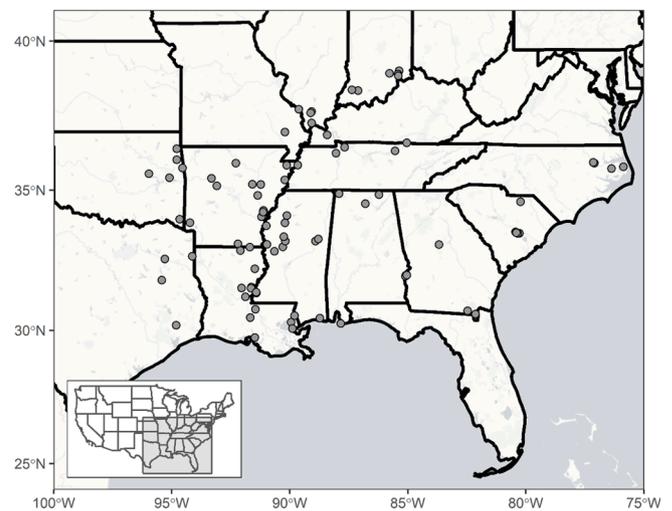


Fig. 1. Centroids of Mobile Acoustic Bat Monitoring program routes (gray dots) on U.S. Fish and Wildlife Service field stations in 14 U.S. states (2012–2017). Base map courtesy of Carto.

also occurred frequently along roadsides, particularly when routes left refuge boundaries.

Survey routes were typically sampled once or twice annually (though occasionally thrice to six times) from June 1 to July 15 from 2012 to 2017. We designed sampling periods to optimize detectability while also minimizing variability by excluding times when non-resident, migratory bats were present, and also to minimize sampling of newly-volant young (U.S. Fish and Wildlife Service, 2012). Repeated sampling events on a route were separated by a minimum of 4 days and not > 20 days. Annual sampling events on a route occurred within a 21-day period similar to the initial year of sampling to promote temporal consistency across years. Surveys began 30 min after local sunset and were typically completed within two hours. Field surveyors implemented continuous acoustic sampling for bats while driving along the survey route at a constant speed of 32 kmh^{-1} to maintain consistency in bat call quality and quantity and allow for assumptions that unique individuals were detected to facilitate estimates of relative abundance (Britzke and Herzog, 2009). Surveys were conducted only when wind speeds were $< 24 \text{ kmh}^{-1}$ and not during rain or fog events.

We used an Anabat SD2 detector (Titley Scientific, Inc.) with a vehicle roof-mounted directional microphone oriented vertically upward to record ultrasonic echolocation during mobile survey routes. The Anabat SD2 detector uses zero-crossing analysis to record ultrasonic vocalizations, and logs detected call files based on pre-determined frequency range divisions (Britzke, 2004; Britzke et al., 2013). Call files were referenced to location and time on a 1-sec interval by connecting an external GPS unit to the Anabat SD2 Detector.

2.2. Bat species classification

We extracted potential bat call files and associated location and time information using the CFCread Storage ZCAIM interface version 4.4n software (Corben, 2011). We set call parameter characterizations in the software to a smooth value of 50, a 1-sec maximum time between calls, and a minimum line length of 5 in CFCread to better quantify pulses representative of an individual bat. As recommended by Britzke et al. (2013), we attempted to use only search-phase calls in species identification by employing a conservative call filtering approach to eliminate pulse fragments and other low quality pulses. We classified call sequences using BCID Eastern USA Version 2.7 software (Allen, 2015). At present, BCID can classify 13 of 16 bat species expected to occur within MABM study area. Northern yellow bat (*Lasiurus intermedius*), Seminole bat (*L. seminolus*), and Brazilian free-tailed bat (*Tadarida brasiliensis*) are

absent from the software. BCID cannot distinguish eastern red bat (*Lasiurus borealis*) from Seminole bat in areas of range overlap. Thus in southern portions of the study area we were likely modeling eastern red bat and Seminole bat as a single species. Similarly, BCID cannot classify Brazilian free-tailed bat, thus some low-frequency species such as big brown bat (*Eptesicus fuscus*) are at risk for misclassification. However, we expect Brazilian free-tailed bat prevalence to be low on refuges as they are uncommon in these environments, and are higher-elevation flyers such that they may not be detected by mobile acoustic detectors. We set the minimum number of call pulses present in a file for classification to 5 to improve accuracy of identification and limit unknown classifications. To further reduce the number of false-positive detections, we constrained classifications at each field station to the suite of bat species potentially present during the sampling period based on species range maps and expert opinions of regional bat researchers (Table S1).

2.3. Analysis of population trend and habitat associations

We restricted our analyses of trends in species counts (as an index of population trend) separately to eastern red bat/Seminole bat (hereafter, the LABO/LASE complex), evening bat (*Nycticeius humeralis*; NYHU), tricolored bat (*Perimyotis subflavus*; PESU), big brown bat (EPFU), and little brown bat (*Myotis lucifugus*; MYLU). We selected these species because they were widespread among MABM routes, consistently detected but with variable activity intensities among routes, and, with the exception of LABO/LASE and NYHU, are potentially susceptible to widespread population crashes due to WNS impacts. We modeled an index of relative abundance based on the count of search-phase echolocation counts using generalized linear mixed models (GLMM; Bolker et al., 2009; Bolker, 2015). We examined the relationship between bat echolocation counts and survey year (the trend in relative abundance; variable year in model below) and survey date within a year (converted to weeks since 1 June; *wk_jun1*). We used 2016 National Land Cover Data (Yang et al., 2018) to quantify the proportion of total woody habitat (upland deciduous, evergreen, and mixed forest, and forested wetland) and developed (urban) habitat (low, medium, and high intensity developed and open space) around each route, weighted by a Gaussian smoothing kernel (Chandler and Hepinstall-Cymermann, 2016) with a standard deviation of 250 m. This produced for each route an estimate of the proportional cover of wooded (*wood_250*) and developed (*urban_250*) habitat within roughly 750 m of the route, but with areas closer to the route contributing more to the estimate (Fig. S2). We used this approach to identify the habitats close to the survey route, which we expected to most influence relative abundance, while also considering a larger landscape context of the route. We included survey route length as an offset in the GLMM, effectively converting our interpretation of relative abundance to a per km basis. We included random intercepts for survey year and route to account for region-wide variation in relative abundance among years and consistent differences in relative abundance among routes, respectively. Finally, we allowed annual trends in relative abundance to vary randomly among routes around an overall trend (i.e., a random slope). Specifically, our model for each species took the form:

$$C_{ijk} \text{Pois}(L_i \times \mu_{ijk}) \text{orNB}(L_i \times \mu_{ijk}, \theta)$$

$$\log(L_i \times \mu_{ijk}) = \log(L_i) + \beta_0 + u_{0,k} + u_{0,i} + (\beta_1 + u_{1,i}) \times \text{year}_i + \beta_2 \times \text{wk}_{jun1} + \beta_3 \times \text{wood}_{250i} + \beta_4 \times \text{urban}_{250i} \quad (1)$$

$$u_{0,k} \sim N(0, \sigma_k^2)$$

$$(u_{0,i}, u_{1,i}) \sim N\left(0, \begin{bmatrix} \sigma_{0,i}^2 & \rho\sigma_{0,i}\sigma_{1,i} \\ \rho\sigma_{0,i}\sigma_{1,i} & \sigma_{1,i}^2 \end{bmatrix}\right)$$

where C_{ijk} is the count of an individual of a species along survey route i on survey occasion j in survey year k , L_i is the length of survey route i in km, and μ_{ijk} is the expected, or mean, count of individuals of a species in a Poisson (Pois) or negative binomial (NB) distribution; θ is the overdispersion parameter of the negative binomial distribution. The β s are the fixed effect parameters estimated for the intercept and variables of interest. The u s are the zero mean normally-distributed random effects, specifically the random intercept by year ($u_{0,k}$) and route ($u_{0,i}$), and the random slope of the population trend by route ($u_{1,i}$). We assumed the latter two random effects may be correlated, expressed by ρ . We fixed ρ at zero for models including MYLU to improve model convergence; MYLU model convergence was impaired due to smaller sample size (i.e., number of stations) resulting from a more limited geographic range.

We explored two negative binomial models (NB1, NB2) in addition to the conventional Poisson model for the count-generating process to consider potential overdispersion in the relative abundance. The distinction between the NB1 and NB2 model is how the variance of echolocation counts relates to the mean of those counts. In NB2 (the “standard” negative binomial model) the variance increases quadratically with the mean, whereas in the NB1 model, the variance increases linearly with the mean (Hilbe, 2011). All models used a log-link function and we assumed a constant detection probability (or that covariates adequately account for variable detection probability; Barker et al., 2018). We also assumed mobile survey routes adequately represented bat populations on and around refuges during the survey season, and that acoustic detectors adequately detected individual search phase calls within a detectable distance from the vehicle. We also assumed that each survey route location was independent, with the exception of the few refuges where multiple sequential routes were in place. In places where multiple routes existed, these were typically surveyed on separate nights or out of sequence. We selected among count distribution models using Akaike’s Information Criteria (AIC; Akaike, 1973). We assessed model residual and other diagnostic plots to further confirm an adequate model fit prior to inference and the use of parameter estimates in the prospective power analysis. We fit GLMM models using the *glmmTMB* package (Brooks et al., 2017) in R (R Core Team, 2018); the *bbmle* (Bolker, 2017) and *DHARMA* (Hartig, 2019) packages facilitated AIC test comparisons and GLMM diagnostics.

2.4. Prospective power analysis

We used the fixed parameter estimates from best-fitting GLMM models for each species to establish a baseline relative abundance for the prospective power analysis. Specifically, we estimated the average relative abundance for a survey conducted in late June 2012 (average survey date; initial year) on a route of average length in a landscape context of average wood and urban cover. The NB overdispersion and random effect estimates informed the power analysis by incorporating how relative abundance varied among sites and years, as well as how estimates of population trends varied among sites. We conducted the power analysis for four bat groups: LABO/LASE, EPFU, MYLU, and PESU and NYHU; we grouped PESU and NYHU into a complex due to the similarity in their expected baseline relative abundance as well as the overdispersion and random effect parameter estimates of their respective GLMM models. We generated 1000 simulations of annual bat declines of 1.14%, 2.73%, and 5% to maintain consistency with other documented power analyses (e.g., Barlow et al., 2015). We simulated sampling effort of 50, 100, and 200 routes, surveyed annually or biennially (every other year) on 2 or 3 occasions per season to evaluate how survey effort influenced our ability to detect declines and affected the accuracy of the estimates of those declines. We assumed a negative binomial (NB2) count-generating process, linear population declines, constant detection probability, and independence among routes. For each simulation, we evaluated whether the model detected a population trend at $\alpha = 0.10$ and, if so, the estimated magnitude and trajectory (i.e.,

increase or decrease) of the trend estimate (Gelman and Carlin 2014). We selected a more conservative α to err on the side of detecting population changes when they were not actually occurring (i.e., we accepted a slightly higher probability of false positives than is typical). Table S2 provides an overview of the power analysis setup. We conducted the simulations using tools provided by the simsalapar package in R (Hofert and Maechler, 2016).

3. Results

Collaborators in the MABM program conducted 736 acoustic surveys across 86 individual routes at 63 FWS field stations in 14 U.S. states from 2012 to 2017. On average, collaborators operated 60 routes annually (range: 53 – 70). We detected a total of 33 921 individuals from search-phase bat calls identified to 13 species across routes and years (Table S3). Survey effort averaged 123 surveys/year and ranged from 102 surveys in 2017 to a peak of 157 surveys in 2013.

3.1. Species trends and habitat associations

Model selection criteria and diagnostics identified the NB2 model as the best fit for all species (Table S4). We detected a substantial annual decline in relative abundance for PESU (-15.1%; 95% CI: -20.6 to -9.1%) and MYLU (-13.9%; 95% CI: -22.9 to -3.8% (Fig. 2; Table S5). Relative abundance increased throughout the survey period each year in all species except NYHU, suggesting within-season temporal increases in bat activity, abundance (i.e., volant young), or detectability (Fig. 2; Table S5). Bat relative abundance associated positively with woody

cover along routes in all species except PESU. The association was particularly apparent in EPFU, with a 35.8% increase in relative abundance (95% CI: 16.1 to 58.9%) for every 10% increase in surrounding woody cover. The association with developed cover along the route was negative in NYHU and LABO/LASE, with 58.5% (95% CI: 36.5 to 72.9%) and 38% (95% CI: 9.7 to 57.4%) declines in relative abundance for every 10% incremental increase in developed land cover, respectively (Fig. 2; Table S5). EPFU relative abundance exhibited a large positive association with developed cover along routes, but the association was extremely variable.

3.2. Power analysis

The MABM program’s ability to detect population change varied considerably with the magnitude of population change, number of independent survey routes, and the duration of the monitoring program (Fig. 3). Under our model, power simulations suggested that 50–100 survey routes may be required to detect a catastrophic decline (-5% annual trend) in our focal bat species over 20 years with adequate (80%) statistical power (Fig. 3C). To detect that same decline in only 10 years of monitoring required at least 100 survey routes for most species (Fig. 3C). However, the simulations suggested > 200 survey routes were required to detect a more modest, but still substantial, decline of 2.73% annually after 20 years; detecting such a decline in 10 years required far greater effort (Fig. 3B). Declines on the scale of 1.14% annually (25% over 25 years) were practically impossible to detect given the current MABM program implementation (Fig. 3A). Relative to the number of routes operated, the power analysis suggested modest power gains from

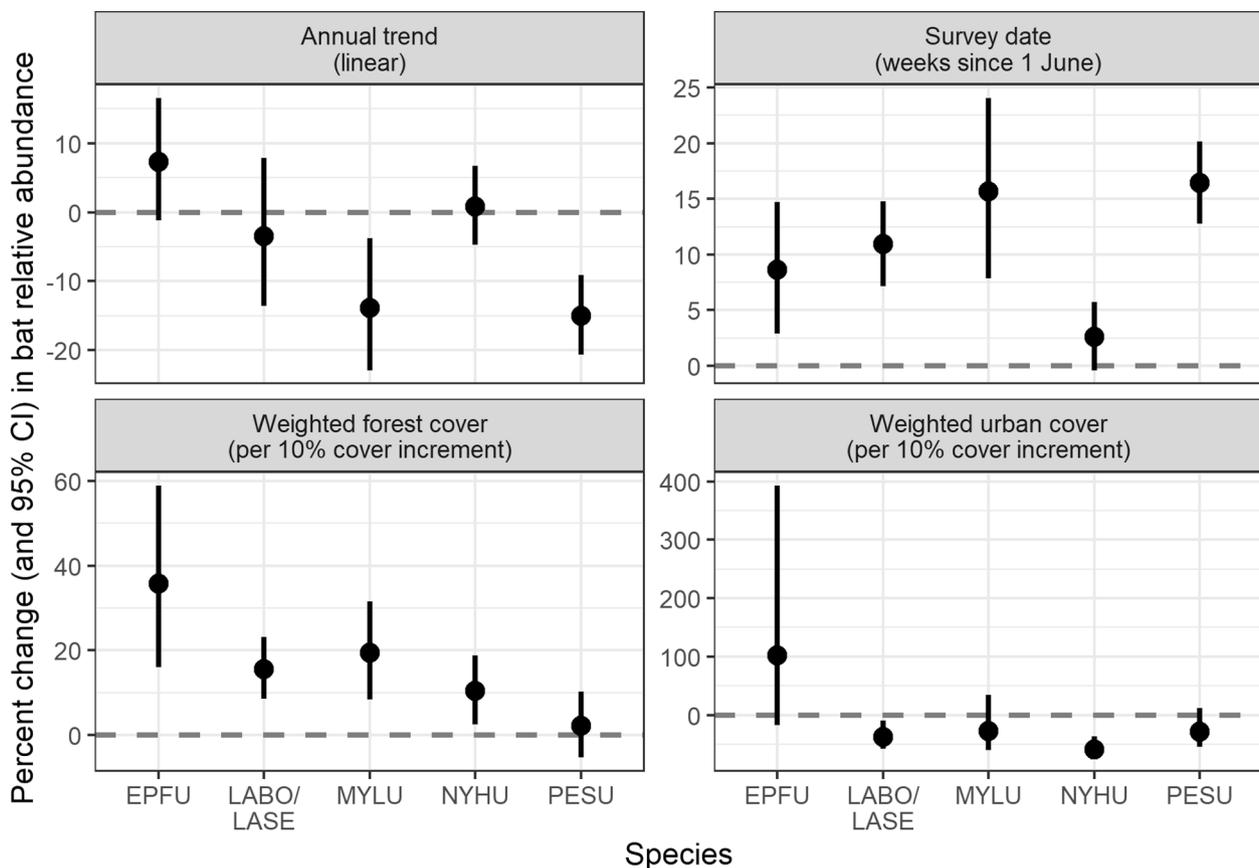


Fig. 2. Percent change in the relative abundance of five bat species based on generalized linear mixed model parameter estimates for annual trend, survey date, and weighted forest and urban cover along USFWS Mobile Acoustic Bat Monitoring program survey routes. Changes associated with survey date and land cover are scaled per week since June 1 and per 10 percent increment in cover, respectively. The horizontal dashed line suggests no association. Bat species include big brown bat (*Eptesicus fuscus*; EPFU), eastern red bat (*Lasiurus borealis*; LABO; includes Seminole bat [*Lasiurus seminolus*] where co-occurring), little brown bat (*Myotis lucifugus*; MYLU), evening bat (*Nycticeius humeralis*; NYHU), and tricolored bat (*Perimyotis subflavus*; PESU).

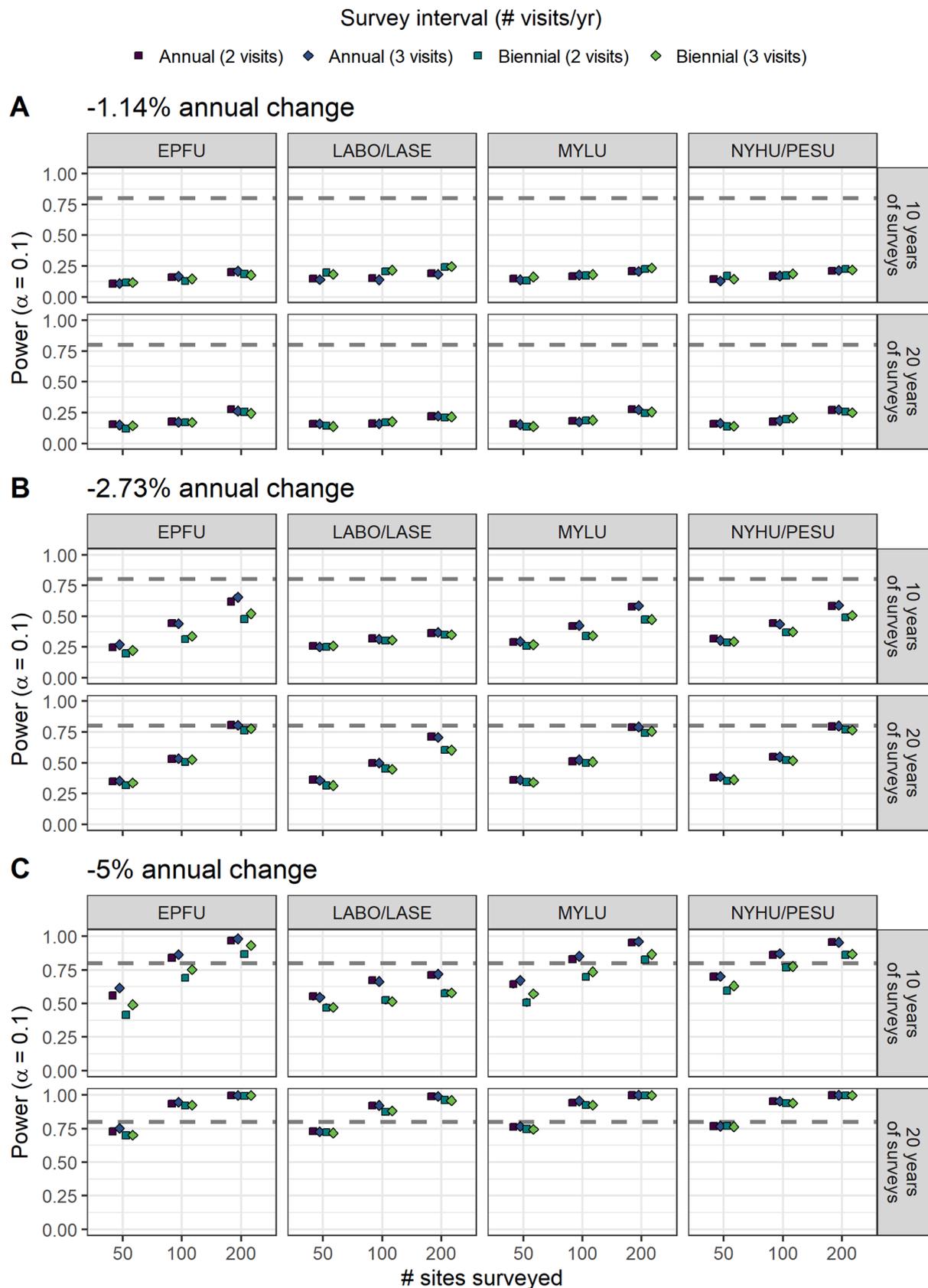


Fig. 3. Outcomes of power analysis based on 2–3 annual or biennial surveys at 50, 100, and 200 sites over 10 and 20 year periods for big brown bat (*Eptesicus fuscus*; EPFU), eastern red bat (*Lasiurus borealis*; LABO; includes Seminole bat [*Lasiurus seminolus*] where co-occurring), little brown bat (*Myotis lucifugus*; MYLU), evening bat (*Nycticeius humeralis*; NYHU), and tricolored bat (*Perimyotis subflavus*; PESU) as part of the U.S. Fish and Wildlife Service Mobile Acoustic Bat Monitoring program (2012–2017).

conducting annual surveys versus biennial surveys, and little benefit of conducting surveys on more than two occasions within a year (Fig. 3).

In addition to failing to detect modest population declines, we suspect underpowered monitoring also produced inflated estimates of trends, or, at least such large CI's that recommendations for management action would be undermined when detected and, in cases of very low power, estimated trends of incorrect direction. We illustrate with an example MABM program of 50 routes surveyed twice annually for 10 years (Fig. 4). Such a program possessed 50 – 75% power to detect a catastrophic 5% annual decline, but low (~25%) and very low (~15%) power to detect 2.73% and 1.14% annual declines, respectively. In the catastrophic context, declines are estimated relatively well (overestimated by 20–30%) and very seldom identified incorrectly as population increased (Fig. 4, bottom panel). However, under more modest population decline scenarios, bias in the trend estimator increased dramatically, as did the tendency of the estimator to incorrectly suggest population growth. Declines were overestimated by 200% and 500%

when they were correctly detected, and incorrectly identified as population growth in ~ 2% and 17% of “significant” trends at 2.73% and 1.14% declines, respectively (Fig. 4).

4. Discussion

4.1. Southeastern bat population trends and habitat associations

Either WNS or the fungal agent *Pseudogymnoascus destructans* has previously been detected in 12 of 13 of our target species in the MABM program in parts of their range, though a range of outcomes from benign effects in some species to large-scale population crashes in others result from *P. destructans* exposure (U.S. Fish and Wildlife Service, 2019). Other threats related to habitat loss, energy development, and changing climate are of equivalent concern. Thus, tracking regional population trends in species threatened by myriad stressors is paramount. We detected 8 of those 13 species so infrequently as to preclude robust

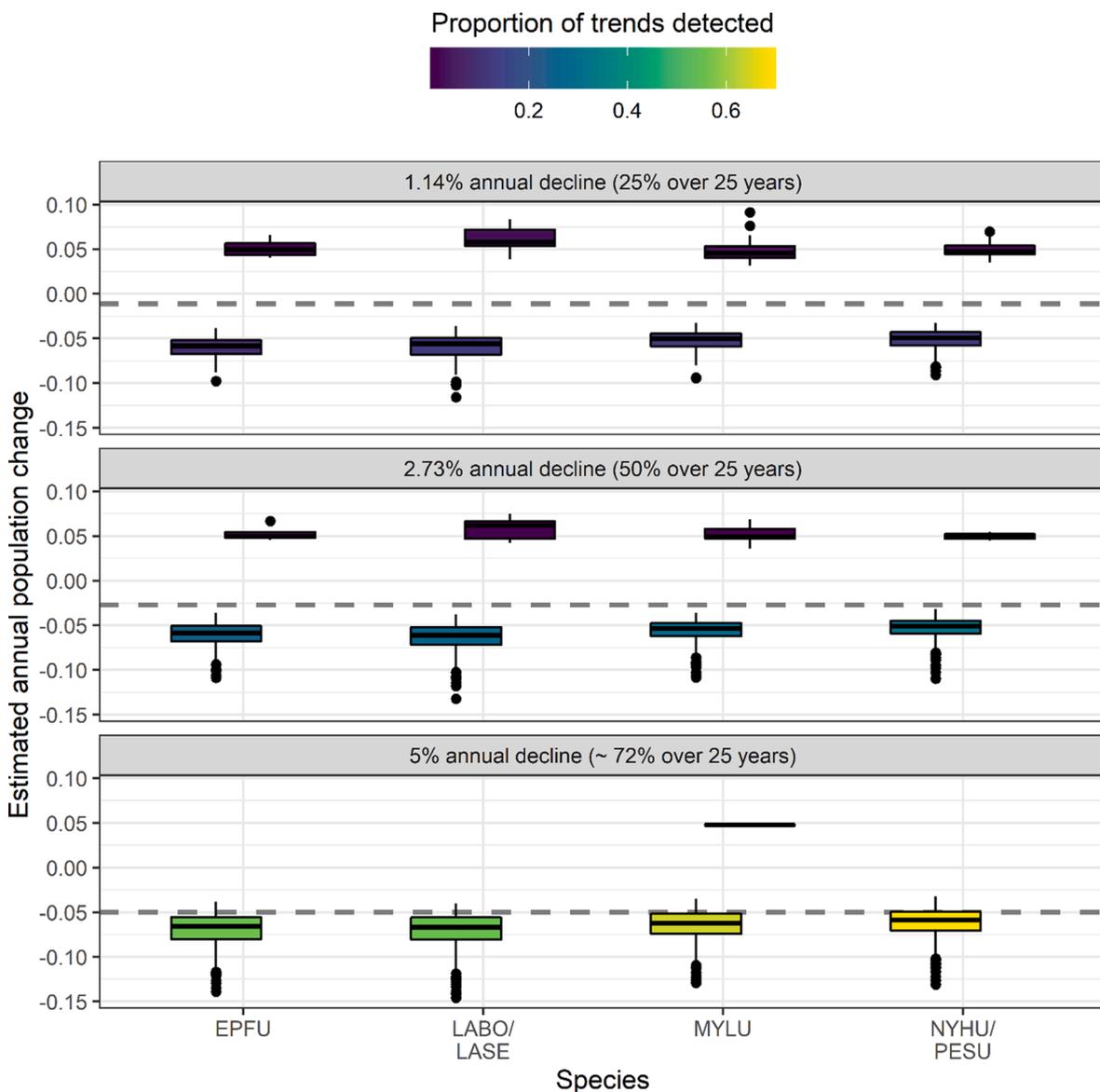


Fig. 4. Power to detect population change (proportion of trends detected) and trend estimates under simulated annual declines of 1.14 – 5% for big brown bat (*Eptesicus fuscus*; EPFU), eastern red bat (*Lasiurus borealis*; LABO; includes Seminole bat [*Lasiurus seminolus*] where co-occurring), little brown bat (*Myotis lucifugus*; MYLU), evening bat (*Nycticeius humeralis*; NYHU), and tricolored bat (*Perimyotis subflavus*; PESU), monitored via a simulated USFWS Mobile Acoustic Bat Monitoring program surveying 50 routes twice annually for 10 years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

population analysis (Rafinesque's big-eared bat [*Corynorhinus rafinesquii*], Ozark big-eared bat [*C. townsendii ingens*], hoary bat [*Lasiurus cinereus*], gray bat [*Myotis grisescens*], eastern small-footed bat [*M. leibii*], northern long-eared bat [*M. septentrionalis*], Indiana bat [*M. sodalis*], and southeastern myotis [*M. austroriparius*]). This is concerning as three of these species have present listing status under the U. S. Endangered Species Act, and all 13 species were considered as a state Species of Greatest Conservation Need (SGCN) in one or more states in our study region as of 2015. This left us to restrict our trend analysis to five species (big brown bat, eastern red bat/Seminole bat, little brown bat, evening bat, tricolored bat), presuming they are representative of the remaining species of interest.

Tricolored bats are obligate cave/deep crevice hibernators in northern parts of their range, and many hibernacula have fallen susceptible to WNS. However, in the Southeast recent research shows tricolored bats regularly use trees, bridges, and culverts for winter torpor, and investigations regarding WNS impacts in these populations are ongoing (Newman, 2020). Despite being widespread in eastern North America, populations have declined an estimated 30–70% since 2006 (NatureServe, 2019). Little brown bats are considered globally endangered by IUCN, with predicted declines of as much as 94% in the next 12–18 years due to effects of WNS (Solari, 2018). They are obligate cave hibernators and often roost in colonies sized in the hundreds of thousands or more, thus have been drastically impacted by the spread of WNS (Solari, 2018). Ford et al. (2011) also showed significant declines in little brown bat after WNS impacted colonies in New York, but did not detect significant declines in tricolored bat or eastern red bat/Seminole bat populations. We found substantial declines in tricolored bat (15.1% annual declines) and little brown bat (13.9% annual declines) on FWS field stations over the 6 year monitoring effort. However, we urge caution in interpreting the estimated declines of tricolored and little brown bat without fully assessing the caveats associated with our power analysis (further discussion in Section 4.3 below). The MABM program effort analyzed here is roughly analogous to the power and estimate accuracy scenario summarized in Fig. 4. A consequence of our underpowered work to date is that we have likely overestimated declines of tricolored and little brown bats, perhaps by up to 30% or more.

With respect to habitat, we found positive associations with developed cover in big brown bats. This finding is supported by previous radio telemetry efforts that suggest human-made structures are important roost habitat for big brown bats (Duchamp et al., 2004). We also found positive associations with woody cover in big brown bats, which suggests a propensity to forage in wooded areas, though many other studies suggest big brown bats to be habitat generalists (see Agosta, 2002 and citations therein). We found negative associations with developed and positive associations with woody cover in evening bats, which tends to roost in tree cavities and forage in forests (Duchamp et al., 2004; Hein et al., 2009). Thus threats of human development and concomitant forest loss/fragmentation could have precipitous negative effects on evening bat populations. Evening bats have also been shown to have negative associations with tree density and positive associations with fire frequency, suggesting they may prefer open forests (Starbuck et al., 2015).

With the exception of one species (little brown bat), all species showed evidence of within-season increases in relative abundance across MABM routes (as also demonstrated by Skalak et al., 2012). We expect these results stem primarily from changes in bat maternal status and the volancy of young, but cannot determine causation without further study. Additionally, we suggest that site selection bias (Fournier et al., 2019) may also contribute to the size of estimated declines in these species. However, it is worth noting that sites were not selected specifically to detect individual bat species, but more so to represent the range of habitats within and nearby southeastern National Wildlife Refuges. Any site selection bias here would be related to variation in habitat cover on refuge lands vs. other non-protected areas in the region. Again, we encourage caution in when interpreting of these results due to

the aforementioned issues with potentially underpowered estimators.

4.2. Large-scale bat monitoring

Large-scale bat monitoring programs can be found worldwide and often are effective in detecting trends of populations of interest. These include standardized, large-scale acoustic monitoring programs in the U. K., Ireland, and eastern Europe (Barlow et al., 2015; Jones et al., 2013; Roche et al., 2011). The recently developed North American Bat Monitoring Program (NABat) is an example of one such program that provides a probabilistic and spatially-balanced grid-based approach, overlaying a continuous grid of 10x10km sampling cells across North America (Banner et al., 2019; Loeb et al., 2015). Despite critically-important continental monitoring efforts like NABat, it remains imperative to have programs that monitor population trends at the scale of management such that adaptive management approaches can be taken to retain and recover bat populations. The FWS MABM program was implemented to provide a regional standardized framework for bat monitoring on FWS field stations. However, the program was initiated prior to the development and launch of the NABat program. Release of a program such as NABat at a continental scale is critically important and a significant advancement for the North American bat monitoring community. It is now necessary to consider Refuge monitoring and management needs in light of the capability to spatially subset the NABat sampling grid on Refuge properties. It will also be important to evaluate the efficacy of stationary vs. mobile acoustic detectors in the two programs in effectively tracking population trends. Thus some creative and proactive thinking must be done to determine if there is a fit for mission-specific monitoring efforts like FWS MABM under a larger monitoring framework like NABat to ensure congruence of data and improve inference to regional bat population trends.

Though methods vary for each of the aforementioned monitoring programs, all make the assumption that they have implemented a robust and repeatable survey design that will allow for reliable inference regarding bat population changes over time. However, the challenges associated with reliably detecting bats come in many forms, including seasonal and daily variation in bat activity (Hayes, 1997; Skalak et al., 2012), variation from type and sensitivity of bat detector (Adams et al., 2012; Barclay, 1999; Barlow et al., 2015), variation in automated classification systems (Russo and Voigt, 2016), and roadside detection bias (Berthinsen and Altringham, 2012; D'Acunto et al., 2018; de Torrez et al., 2017; Roche et al., 2011; Stahlschmidt and Brühl, 2012). Automated classification could be particularly problematic in this case as we must assume that call filtering parameters and classifiers produced no false negative or false positive species identifications within the BCID software program. Though we did account for this potential issue using species grouping, other false positives and/or negatives, if widespread, could artificially inflate or deflate relative abundance estimates. This could be improved in future monitoring efforts through vetting against known calls at the site level. The design and analysis presented here also does not account for imperfect detection as a potential source of variation, which may risk underestimation of measures of abundance and introduce bias in assessing interactions with environmental variables (Rodhouse et al., 2012; Yoccoz et al., 2001). Though most MABM survey routes were sampled twice or more per season, we were not able to assess detectability within a single year in this analysis. However, provided that our interest was in assessing trend as a state variable of interest, measures of detectability were not required. We also could not fully assume population closure within each survey season, hence why we did not pursue a N-mixture model approach to analysis. Nevertheless, mobile transects can be efficient; they require little training, allow surveyors to cover a greater distance in a shorter amount of time, may detect greater numbers of species compared to other approaches, and can account for spatial variation by georeferencing detection locations (D'Acunto et al., 2018; Whitby et al., 2014). Given the caveats, the utility of road-based acoustic surveys for bats depends on monitoring

objectives in the context of available monitoring resources and the cadre of potential sources of variation in the data (Whitby et al. 2014).

4.3. Statistical power to detect population change

What constitutes acceptable statistical power for a monitoring program requires determining the level of risk one is willing to take in failing to detect a significant trend, and/or detecting exaggerated or incorrect trend estimates (Britzke et al., 2013; Gelman and Carlin, 2014; O'Donnell and Langton, 2003). Understanding a given monitoring program's power to detect a desired trend prior to implementing that program will help ensure available resources align with required sampling effort to increase efficiencies and effectiveness (Magurran et al., 2010). However, power analyses should be continually updated based on best available data, which includes refinement of models defining parameter coefficients that inform the power analysis. Nevertheless, prospective power analysis should be considered as a fundamental component to planning and execution of any long-term monitoring program (Legg and Nagy, 2006).

We sought to examine whether the current sampling effort under the FWS MABM program provided sufficient statistical power to detect specified levels of population change for bat species in the eastern U.S., as well as estimate the sampling effort needed to detect those changes. We found we could detect catastrophic (-5%) annual declines with 80% statistical power by surveying 50–100 sites twice annually over a 10 year or greater period for four of the five most-commonly detected species (tricolored bat, evening bat, big brown bat, little brown bat). To detect this same level of decline in eastern red bat/Seminole bat would require sampling over a 20-year period despite detecting >10 times the number of individuals compared to little brown bat. We also estimated it would take > 20 years and > 200 sampling sites to detect population declines of lesser magnitude for all species examined. Thus, the current FWS MABM program is likely capable of detecting major population changes in the most widespread and common bat species, but may be insufficient to track changes of lesser magnitude in common species or any magnitude of population change in more localized or uncommonly detected species. Note that these estimates are contingent upon the fit of the statistical model to the populations represented by the MABM program. Simulations in our power analysis did not account for habitat or time covariates, nor were we able to assess the sensitivity of the power analysis to the original inclusion of habitat and time covariates in original parameter estimates. Nevertheless, this relative lack of power in detecting all but the most severe population declines highlights an underappreciated but universal phenomenon—magnitude or exaggeration errors (see Gelman and Carlin, 2014) that characterize estimates of population change in underpowered monitoring programs. The magnitude of “significant” population changes may be exaggerated, often exceedingly so, in underpowered monitoring programs and, in the worst cases, may suggest a trend in the opposite direction of reality. This phenomenon applies equally to other parameters estimated along with population change (e.g., habitat associations, detection probability, etc.). However, given the contingency of power analyses estimates on the statistical model on MABM program data, we encourage other efforts to consider developing a new project-specific model for other power analysis endeavors.

Results from other bat monitoring efforts are similar to what we observed in the MABM program, despite differences in monitoring strategy. Banner et al. (2019) demonstrated that regional sampling efforts (>181 stationary sites) under NABat tended to be adequately powered, but a subset of < 30 sites on National Forest lands resulted in underpowered estimates of change in occupancy. The U.K. National Bat Monitoring Program found that 200 monitoring sites surveyed using multiple methods over 9 years were sufficient to detect 5% annual declines in three of their more common species, but that upwards of 18 years would be required to detect declines of lesser magnitude at 80% power (Barlow et al., 2015). A similar analysis for the Irish Bat

Monitoring Programme suggested catastrophic declines could be detected in as few as 8 years with 25 survey grids containing 20 mobile transects each (Roche et al., 2011). Though these examples cover a range of bat monitoring methods and are not directly comparable to MABM program transects, the consistent message that very large and long-term monitoring programs may be paramount in detecting changes of lesser magnitude (e.g., 1–3% per year), with recommendations of as many as 500 or more sample sites monitored over more than a decade to effectively track change (O'Donnell and Langton, 2003).

5. Conclusions

Monitoring programs should make every effort to maximize accuracy while minimizing misguided inference about population trends (O'Donnell and Langton, 2003). A successful monitoring program should be repeatable, straightforward, and developed on the basis of a long-term commitment to estimation and evaluation of species trends over time. It should also be conducted at the appropriate scale of application to meet programmatic objectives (e.g., informing Refuge management vs. detecting regional or continental trends). We showed that significant commitments to long-term monitoring efforts are necessary to even detect the most catastrophic of declines in bat populations. Statistical power is a serious issue for monitoring bat populations and continues to deserve consideration prior to the implementation of large-scale monitoring efforts.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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