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Integrating Multiple Survey Techniques to Document a Shifting Bat Community in the Wake of White-Nose Syndrome

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Abstract

The long-term study of bat communities often depends on a diverse set of sampling methodologies that are chosen based on the species or habitat management priorities of the research project. Integrating the data from a diverse set of methodologies (such as acoustic monitoring and mist net sampling) would improve our ability to characterize changes in community structure or composition over time, such as one would expect following an emergent infectious disease such as white-nose syndrome. We developed a Bayesian state-space model to integrate these disparate data into a common currency (relative abundance). We collected both acoustic monitoring and mist net capture data over an 8-y period (2006–2014) to document shifts in the bat community in central New England, USA, in response to the onset of white-nose syndrome in 2009. The integrated data model shows a significant decline in the abundance of little brown bat *Myotis lucifugus*, northern long-eared bat *Myotis septentrionalis*, and hoary bat *Lasiurus cinereus*, and an increase in abundance of the eastern small-footed bat *Myotis leibii* and the eastern red bat *Lasiurus borealis*. There was no evidence for a change in abundance in the big brown bat *Eptesicus fuscus* since the onset of white-nose syndrome. The consistency of this model with regional estimates of decline over the same time period support the validity of our relative abundance estimate. This model provides the opportunity to quantify shifts in other communities where multiple sampling methodologies were employed, and therefore provides natural resource managers with a robust tool to integrate existing sampling data to quantify changes in community composition that can inform conservation and management recommendations.

Keywords: acoustic monitoring; bat detectors; mist nets; occupancy models; population surveys

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Introduction

Most studies involving bat communities are part of a specific project or management goal, and therefore generally only provide a snapshot of the spatial or temporal bat abundance within the area. Where multiple surveys have been conducted within a single area, they often reflect a diversity of sampling methodologies that were based on the species or habitat management priorities of the survey. For example, many bat research projects collect acoustic monitoring data over a broad area and then use mist net capture of bats to collect demographic data on target species. Although these mist net capture data are often based on the results of acoustic monitoring studies, there is no common metric available to integrate the two data sets. Collectively, these data can provide valuable presence-absence information on rare species, but the data generally are not combined into a single index of bat abundance or species diversity because of their disparate sampling methodologies. Long-term population surveys are a critical tool for natural resource managers to make informed conservation decisions, particularly when populations may be suffering unusual declines (Blaustein et al. 1994). For bat communities throughout eastern North America, white-nose syndrome (WNS) represents a conservation and management challenge on an unprecedented scale. White-nose syndrome was first documented in New York in 2006 (Blehert et al. 2009) and has since been confirmed in 35 states and 7 Canadian provinces (USFWS 2019). White-nose syndrome has caused a precipitous decline in multiple species of hibernating bats (Turner et al. 2011; Ingersoll et al. 2016).

White-nose syndrome is an emergent infectious disease of hibernating bats caused by the psychrophilic fungus *Pseudogymnoascus destructans* (Lorch et al. 2011; Langwig et al. 2015). The hyphae of *P. destructans* cause lesions on the skin of infected bats that ultimately invade the underlying dermal tissue with little to no immune response (Wibbelt et al. 2010; Meteyer et al. 2012; Pikula et al. 2017). Although the exact mechanism of mortality is unknown, *P. destructans* appears to have a negative impact on the water budget of infected bats, causing dehydration through evaporative water loss (Cryan et al. 2010; Ehlman et al. 2013). There is also evidence that *P. destructans* negatively affects the energy budget during hibernation by disrupting homeostasis and altering the frequency and length of periodic arousals (Blehert et al. 2009; Bohn et al. 2016; Lilley et al. 2016). Although some species of hibernating bats have experienced declines of more than 90% of their population, *Myotis leibii* and *Eptesicus fuscus* have seen lower levels of decline

(Langwig et al. 2012), resulting in dramatic shifts in both species abundance and community structure throughout the Northeast (Frick et al. 2010; Brooks 2011; Moosman et al. 2013; Nocera et al. 2019a). Previous attempts to quantify the shift in species composition have been limited because each study used a single survey technology. Frick et al. (2010) relied on long-term mark-recapture of bats within a summer maternity roost of *Myotis lucifugus* to generate demographic rates that documented the decline and potential extirpation of the species. Although this study generated demographic data that have proven valuable for predicting the impacts of WNS, it is limited to only a single species. Moosman et al. (2013) collected data over multiple years using mist net captures to document the impact of WNS on a bat community but was still limited to only a few species of hibernating bats. Lastly, Brooks (2011) and Nocera et al. (2019a) utilized multiyear acoustic monitoring data to document shifts in bat community structure after the detection of WNS. Although each of these studies documented shifts in either species abundance or community structure based on a specific sampling technique, the lack of statistical methods to compare data collected using diverse methodologies has limited our ability to quantify the impact of WNS on bats in the Northeast, and therefore predict the likely impact of WNS as it spreads across North America. This is particularly true in the context of rare or endangered species, which often require long-term surveys using a variety of complementary methodologies to generate sample sizes required to detect population shifts. The two most common methods of surveying bats on the landscape are mist net captures and acoustic monitoring.

Sampling bats using mist nets or other capture methods (harp traps or roost capture) is necessary when the primary research goal is to obtain demographic, molecular, or physiological data on individual bats. Mist nets are the most common method of capturing bats because they can be deployed in a variety of ways to effectively sample bats commuting or foraging relatively close to the ground (Kunz et al. 2009). Having bats in the hand is also the most definitive method of confirming the presence of cryptic species that may be difficult to confirm using less direct sampling methods. Although capturing bats in mist nets has many advantages over other survey methods, it is labor-intensive, limited to certain habitats or sampling environments, and shows species-specific sampling biases (Hayes et al. 2009).

Acoustic monitoring surveys have several advantages over capture surveys, including lower cost per unit sampling effort and being less invasive to the bats (Boye 2004; Ford et al. 2011). Acoustic surveys can be deployed



in habitats that are not easily sampled by mist nets (e.g., over deep water or in open fields) and can be conducted at multiple sites simultaneously, or for multiple consecutive nights, without any substantial increase in effort, giving most acoustic sampling surveys broader temporal and spatial coverage (Brooks 2009; Nocera et al. 2019b). At the site level, acoustic monitoring surveys are also more spatially extensive than capture surveys because the detection range of a typical bat detector (approximately 15–40 m; Larson and Hayes 2000; Clawson 2001) provides a much larger sampling area than a mist net. Where both acoustic monitoring and mist net captures have been deployed simultaneously, acoustic monitoring generally indicates greater species diversity than mist netting (Hickey and Neilson 1995; Everette et al. 2001; Sedlock 2001; LaGory et al. 2002).

Acoustic monitoring also has several limitations, including the inability to provide demographic data or direct information on the relative abundance of species. There is also growing awareness that different automated software packages can generate significantly different estimates of community composition (Lemen et al. 2015; Rydell et al. 2017). This is particularly true when species in the same geographic area have overlapping call signatures, such as many species within the genus *Myotis*, or when call signatures converge as a result of similar ecomorphological constraints, such as calls collected in highly cluttered environments (Barclay and Brigham 2004). In these situations, acoustic monitoring can provide ambiguous or erroneous species identification that can affect the effectiveness of conservation and management decisions (Jennings et al. 2008; Russo and Voigt 2016; Rydell et al. 2017; Nocera et al. 2019b). Given the benefits and limitations of each of these survey techniques, acoustic monitoring and mist net sampling are generally considered to be complementary methods that provide a complete and balanced estimate of a bat community (Kuenzi and Morrison 2003; Flaquer et al. 2007; Rodhouse et al. 2012).

When research projects are conducted on bat communities, the sampling methodologies often change over time as the research priorities shift from community structure to management of rare or endangered species. The shift in research priority often involves a shift in methodology, so it is difficult to combine these survey records into a single data set. Nonetheless, some critically important questions can only be addressed by combining these distinct data sets to form a long-term time series. The present study provides an excellent case in point, whereby the dominant sampling method prior to the onset of WNS (mist net surveys) differed from the sampling method employed afterward (acoustic transects and fixed acoustic stations). Therefore, characterizing the impact of WNS on this bat community required a method for integrating these data types. The goal of the current study was to develop an occupancy model that could combine data collected using common sampling protocols into a single index of bat abundance. Occupancy models have proven valuable in habitat management for bats (Bellamy et al. 2013) but thus far they have been limited to a single sampling technique

and they do not have a temporal component that allows us to track changes in species abundance or community evenness over time.

Study Site

The New Boston Air Force Station (NBAFS) is a 1,114-ha military facility located in Hillsborough County, New Hampshire (42°56'N, 71°38'W; Figure 1). Average annual temperature is 8.0°C with monthly averages ranging from −5.2°C to 21.0°C and precipitation averaging 111 cm annually, distributed relatively evenly throughout the year (LaGory et al. 2002). Although the Operations Area is highly developed, the habitat outside this core area is typical for the surrounding region, with a rural land-use pattern of residential areas interspersed with agriculture and forests. The NBAFS is approximately 90% forested, with the dominant vegetation community being mixed maple–beech *Acer* spp.–*Fagus* spp. forest. There are abundant wetland and open water areas within NBAFS, with a combined area of approximately 80 ha (LaGory et al. 2002). The two most dominant features at NBAFS are Joe English Pond (17 ha) located at the center of the site and Joe English Hill (389 m asl and approximately 275 m agl) in the northwestern corner of the NBAFS.

Methods

Bat captures

We conducted mist net sampling at 112 sites for two summers prior to the onset of WNS (2006, 2007, $n = 61$) and two summers after WNS (2012, 2013, $n = 51$) was documented in New Hampshire. The pre-WNS mist net sampling at NBAFS was focused on documenting the bat community (by choosing sites that represented the habitat diversity of NBAFS) or monitoring the impact of specific habitat management goals (such as prescribed burns or selective logging activities: Veilleux et al. 2009; Thomas et al. 2012). After the onset of WNS, mist net sampling sites were focused on resampling pre-WNS sites that had high levels of bat activity. At each sampling site, we captured bats using 38-mm mesh, 2 ply-50 denier nylon mist nets (Avinet, Inc., Dryden, NY) of multiple sizes and configurations depending on the habitat being sampled. We deployed mist nets horizontally in 6-, 9-, 12-, and 18-m lengths either alone (2.3-m height) or as double (4.6-m high) or triple-stacked (6.9-m) nets. We also deployed some mist nets vertically as canopy nets that were 2.3 m wide and 9 m or 12 m high. Except when sampling over water, we designed the mist net configuration to enclose both the horizontal (trail or road width) and vertical (canopy height) space that would be used by commuting bats. For open water sampling sites, the goal was to maximize the total length of the net to capture bats foraging and drinking near the surface of the water. We deployed all mist nets when bats were presumed to be residents at NBAFS, which we defined as beginning 15 May and ending 15 August each year.



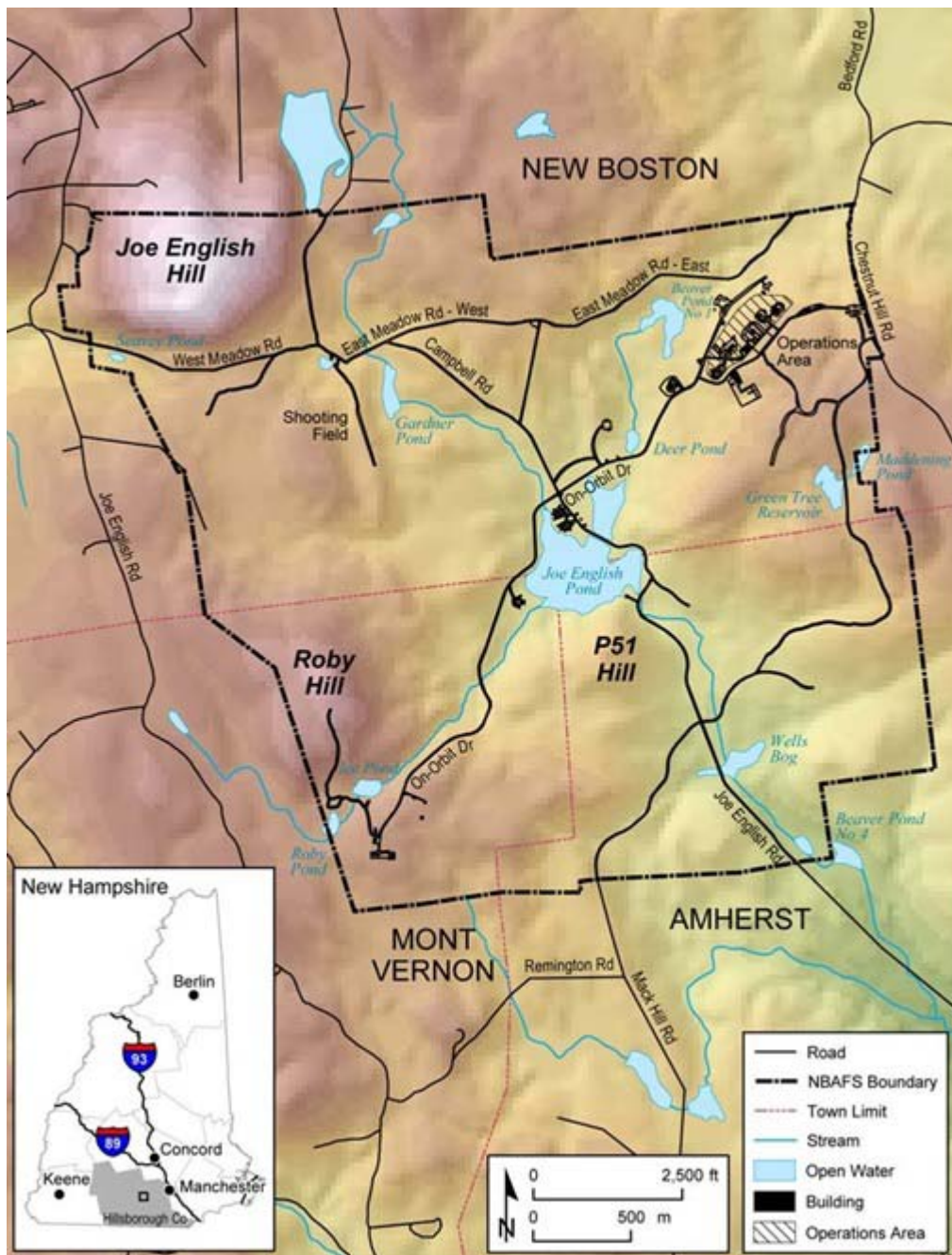


Figure 1. Map of New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, where bats were surveyed from 2006 through 2014.

We opened mist nets approximately 15 min before sunset and kept them open ≥ 5 h each night. We conducted all mist net sampling on evenings with little or no precipitation and ambient temperatures that remained above 10°C during the sampling period. We conducted sampling throughout the lunar cycle and conducted no open water or field edge sampling on nights with strong wind speeds (> 3 m/s). For mist net surveys, each net deployment represented a discrete sampling unit, in which the total captures of each species

was the primary response variable. We computed survey effort by multiplying the total net area by the deployment duration in nights (survey effort was therefore in units of nights $\times$ m²). We obtained permits for this research from New Hampshire Fish and Game and the U.S. Fish and Wildlife Service. All mist net capture and bat handling protocols used at the NBAFS after 2008 were consistent with the isolation and decontamination protocols found in the White-Nose Syndrome National Response Plan (USFWS 2011).

Acoustic surveys

After the onset of WNS in 2008, the majority of data collected at NBAFS were generated using acoustic surveys to minimize the stress on the bats and to reduce the potential for contamination and spread of *P. destructans* from mist nets and handling protocols. Acoustic monitoring was conducted across five summers (2010 through 2014) using ultrasonic transducer microphones attached to either Anabat II or Anabat SD1 detectors (Titley Electronics, Ballina, New South Wales, Australia) with a compact flash Zero Crossing Analyses interface or integrated compact flash data storage, respectively. We conducted both active (monitoring with the researcher holding the detector) and passive (monitoring with a detector left unattended overnight) monitoring using three different monitoring protocols—active transect monitoring, short-term passive monitoring, and long-term passive monitoring.

We conducted the active transect survey in 2010. We chose 15 fixed sampling sites along a linear transect based on their potential for high levels of bat activity. All sites were along forested trails and roads and separated by 300–1,500 m to ensure spatial independence and allow < 5 min travel time between samples using an ATV. On a given night, we sampled each of the 15 sites in order, although we changed the starting location for each survey night to minimize the influence of timing on the bat activity. At each sample site, we surveyed the area for 10 min by holding a microphone, attached to an Anabat SD1 detector with a 3-m shielded cable, parallel to the ground at elbow height (roughly 1.5 m above ground) and moving in a clockwise rotation to survey the entire area. When we heard a bat on the external speaker of the detector, we (the researcher) moved in the direction of the call and attempted to track the bat. Once the call was out of range, we resumed moving the microphone in a clockwise rotation until another call was detected or the end of the sampling period. Sampling did not begin until ≥ 30 min after sunset and total survey time was generally < 4 h/night.

We conducted short-term passive monitoring at 40 locations from across 4 summer periods (2011–2014) with an average of 3.6 nights (range = 1–8 nights) per location. We chose acoustic sampling sites to maximize bat activity (by sampling across forested trails, forest edge habitat, or over open water) within general sampling areas that were identified to maximize spatial and habitat diversity across NBAFS. Each short-term monitoring site had an Anabat detector within a watertight box connected to the transducer microphone by a 3-m shielded cable. Each microphone was mounted on a 1.5-m pole and housed in a weather-tight protective shroud (Bat-Hat, EME Systems, Berkeley, California) that prevented moisture from collecting on the transducer.

We conducted long-term passive monitoring from 1 to 3 locations from 2011 to 2014, with an average of 214 nights (range = 72–365 nights) per location. The long-term monitoring stations were in a V-shaped configura-

tion with the vertex near the southeast corner of Joe English Hill and the north and west sampling stations 900 m and 300 m, respectively, from the southeast station. At each sampling station, we enclosed an Anabat detector in a NEMA-4 watertight housing (Fibox, Inc., Glen Burnie, Maryland) powered with a 35 A-hr battery maintained by a 30-W solar panel. We connected the detector to a pre-amplified transducer microphone by a 10-m shielded cable. We mounted each microphone on a 2.0-m pole and housed it in a Bat-Hat shroud. We oriented the microphone at each long-term monitoring site so that maximum sensitivity of the microphone was facing an uncluttered space with at least 180° of the sampling area with > 5 m of nonvegetated habitat.

Before and after each survey season, we calibrated all microphones and cables in a laboratory setting using a Binary Acoustics AT-100 multifrequency tonal emitter (Binary Acoustics Technology, Las Vegas, Nevada) to confirm minimum performance standards for six different ultrasonic frequencies (20 kHz, 30 kHz, 40 kHz, 50 kHz, 60 kHz, and 70 kHz) at 5 m from the emitter source. In addition, we verified a minimum cone of receptivity (15° off-center) by rotating the microphone horizontally on a platform using the AT-100 as a sound source. In addition, we tested all Anabat detectors in a laboratory setting for relative sensitivity at 40 kHz using a calibration microphone to confirm that all field units had similar sampling ranges and sensitivity.

We analyzed the acoustic data using EchoClass v3.1 (U.S. Army Engineer Research and Development Center, Vicksburg, Missouri) with the Species Set 2 for north-eastern bat species. Some researchers have suggested using multiple software packages to cross-validate species identification (Lemen et al. 2015). Although this is an appropriate recommendation when using automated classifiers to determine the presence of a species across an entire night or sampling period, it is not valuable when attempting to resolve species identification at the file level because of low levels of congruence between software packages (Lemen et al. 2015). All files that were identified to species by EchoClass were attributed to those species without further analysis. All files that were categorized as Unknown by EchoClass were manually reclassified by one of the authors (DSR) based on the File Level Information output data. We limited our reclassification to files that had at least three pulses that were identified to species by EchoClass; this is consistent with filtering criteria used with acoustic data (Law and Chidel 2002; Gannon et al. 2003), although our filter was more conservative because it restricted the analysis to pulses that were identified to species.

We used the EchoClass file output data to reclassify all calls that had $\geq 50\%$ of the individual pulses categorized as High and ≥ 3 individual pulses assigned to bats within the genus *Myotis* (MYLE, MYLU, MYSE, and MYSO). For files that met these criteria, we generated a probable species identification by assigning that file to the species that represented $\geq 67\%$ of the individual pulses. Files

that met the 50% High criterion but not the 67% To Species criterion we assigned as *Myotis* spp. Files that met neither criterion we maintained as Unknown and eliminated from further analysis. To validate this approach, we (DSR) manually analyzed a subsample of 10 reassigned files for each of the 3 *Myotis* species from the 2011–2012 sampling period. Although some of these files could not visually be assigned to a single species with high confidence, all the files had frequency and slope characteristics that were consistent with the reassigned value.

We retained only those acoustic detections occurring during the summer active season (15 May–15 August) to develop the model. For short-term monitoring sites deployed for less than three nights (both passive and active transect surveys), we summarized acoustic detections (total file counts) for the entire deployment period, and computed sampling effort as the total deployment duration in nights. For short-term monitoring sites deployed for more than three nights and for all the long-term monitoring sites, some of which were deployed for an entire calendar year, we summarized the total acoustic detections within three-night sampling intervals to match the most common sampling duration for mist net surveys in this study.

To further enhance the comparability of the acoustic and mist net data, we made two additional modifications. First, to reduce serial autocorrelation in the acoustic data (correlation in the numbers of bats detected by a given acoustic station in consecutive three-night periods), we rarefied the data such that, for a given acoustic station, we selected only a single three-night sampling interval every six nights during the summer roosting season. In addition, to reduce the problem of multiple consecutive detections of the same individual at a microphone, we summarized acoustic data over 15-min intervals as a binary presence–absence for each species prior to generating total counts over the sampling period. Similar presence–absence activity indices have been used in other bat acoustic surveys to reduce the autocorrelation of acoustic monitoring data (Miller 2001; Downs and Racey 2006; Williams et al. 2006). We chose the specific 15-min sampling interval to represent the sampling interval of the typical mist net because each net was checked every 15 min.

Relative abundance model

In our model, annual relative abundance for each bat species was modeled as an unobserved (latent) variable. We were unable to estimate the per capita detection probability (and therefore absolute abundance) for any bat species because of the very low recapture rate in the mist net surveys (seven total recaptures over the entire study period). To enable the estimation of relative abundance, we set the total abundance of the most commonly captured species (*E. fuscus*) to an arbitrary large number (1,000) during the 2-y sampling period during which both acoustic and mist net captures

occurred simultaneously (2012 and 2013). This procedure enabled the statistical algorithm to generate a unique estimate of capture probability (see below), and thereby estimate the annual relative abundance of each bat species. Note that, while arbitrary, the specific anchor value selected had no effect on the analysis as long as the number was much larger than the largest number of detections in a single sampling period. Relative abundance was modeled in three ways: (1) relative abundance was estimated separately and independently for each survey year, (2) relative abundance of each species was modeled as a log-linear trend over time, and (3) relative abundance prior to the onset of WNS (2008) was modeled separately to the relative abundance after 2008.

We computed the expected number of bats of species s captured per unit standard sampling effort during survey interval i as the product of per capita detection probability p_i (representing the probability of capture for a standard-effort sampling bout) and the abundance $N_{s,y}$, where $N_{s,y}$ represents the abundance of species s in year y . We defined a standard-effort mist net survey as a net of dimensions 9.0×2.0 m deployed for three nights, and we defined a standard-effort acoustic survey as a microphone deployed for three nights. We assumed the observed number of bats to follow a Poisson distribution with the expected count (λ) equal to the expected number of bats observed per unit of standard sampling effort ($p_i \times N_{s,y}$) multiplied by the sampling effort:

$$\text{Count}_{s,i} = \text{Poisson}(p_i \times N_{s,y} \times \text{effort}_i)$$

We modeled the detection probability for a single standard-effort survey interval separately for acoustic and mist net surveys, following a standard logistic regression formulation:

$$\text{logit}.p_{s,i} = \text{logit}.p_0 + \beta_1 \times \text{Tavg}_i + \beta_2 \times \text{precip}_i + \beta_3 \times \text{WindSpeed}_i + \text{Tree}_s$$

where $\text{logit}.p_0$ denotes the mean detection probability on the logit scale, estimated separately for mist net or acoustic surveys, corresponding to survey bout i (either m^2 -nights for mist net sites or nights for acoustic sites), Tavg_i represents the average daily temperature ($^{\circ}\text{C}$) for survey bout i , and WindSpeed_i represents the mean daily average wind speed (m/s) for survey bout i (see Table 1 for more details). The logistic regression terms relating detection probability to weather conditions (β_1 through β_3) were each estimated jointly for mist net and acoustic surveys. The calls of migratory tree bats (eastern red bat *Lasiurus borealis*, hoary bat *Lasiurus cinereus*, and silver-haired bat *Lasionycteris noctivagans*) tend to be louder, and thus more readily detected than the other bats in this community; therefore, we added a term (Tree_s) such that the base per capita detection probability of the tree bats was estimated separately from the other species.

To accommodate zero-inflation within both the mist net and acoustic count data sets, we estimated an additional parameter q reflecting the probability of zero

Table 1. Summary of variables measured at mist net and acoustic sampling stations at the New Boston Air Force Station (NBAFS) in New Boston, New Hampshire (2006–2014).

Variable name	Description
Tavg ^a	Mean daily temperature (°C), averaged for the sampling period (max. of 3 nights)
Precip ^a	Daily precipitation (mm), averaged for the sampling period (max. of 3 nights)
WindSpeed	Daily average wind speed, averaged for the sampling period (max. of 3 night).
SurveyEffort	For mist nets: total net area (length × height) multiplied by deployment period in nights. For acoustic stations: total deployment duration in nights.

^a All weather variables were summarized on the basis of daily records from the National Oceanic and Atmospheric Administration weather station at the Manchester Airport, Manchester, New Hampshire (located approximately 15 km east of the study area; see Data A5, *Archived Material*).

total captures (no captures of any species for a given sampling period). We then assigned each survey period i a binary value z_i (distributed as a Bernoulli random variable with probability q) representing whether or not that survey period resulted in zero captures. Thus, the final per capita detection probability model could be characterized as follows:

$$p_{s,i} = 0(\text{if } z_i = 0)$$

$$p_{s,i} = 1[1 + \exp(-\text{logit}.p_{s,i})](\text{if } z_i = 1)$$

Following the convention for regression analyses in WinBUGS, we standardized all covariates (mean = zero, standard deviation = one) prior to analysis. We assigned the abundance parameter $N_{s,y}$ a wide uniform prior distribution, varying from ca. 100 to 10,000. The exception, as noted above, was the abundance of big brown bats in years 2012 and 2013, for which all prior probability weight was assigned to the reference value 1,000 as an anchor point for estimating detection probabilities (otherwise there would not be a single unique solution). All other free parameters were assigned noninformative uniform, normal, or beta distributions (Table 2).

We estimated all model parameters with Markov chain Monte Carlo (MCMC) using WinBUGS 1.4 (Lunn et al. 2000), which we called from the Program R environment

via the R2WinBUGS package (Sturtz et al. 2005; R Core Team 2016). We ran three independent Markov chains, discarding the first 25,000 MCMC samples as a burn-in and storing every fifth sample of the remaining 25,000 MCMC iterations for further analysis. We tested for convergence of the Markov chains to the stationary posterior distribution with the Gelman–Rubin diagnostic and summarized the posterior distributions for all parameters with the mean of all MCMC samples as a point estimate and the 2.5 and 97.5 percentiles of the MCMC samples as a 95% credible interval (Bolker 2008).

Results

Bat captures

A total of 321 bats of 6 species (*E. fuscus*, *M. lucifugus*, *M. leibii*, *M. septentrionalis*, *L. borealis*, and *L. cinereus*) were captured across 212 net-nights conducted during the period of summer residency from 2006 to 2013 (Table 3; Data A1 and Data A2, *Archived Material*). Catch per unit effort peaked in 2007 at 5.39 bats per standard 3-night mist net survey, and it was lowest in 2013 at 3.15 bats captured per standard survey. Surveys conducted in 2002 had much lower catch per unit effort (< 1 bat captured per standard survey), and these surveys were not considered for further analysis because the 2002 population survey was a pilot study intended to identify

Table 2. Parameters for the Bayesian model of relative bat abundance at New Boston Air Force Station (NBAFS) in New Boston, New Hampshire (2006–2014). Relative abundance, summarizing prior distributions and posterior distributions by mean and 95% credible interval (CI).

Parameters	Specified Prior distribution	Prior, Mean	Prior, Low bound 95% CI	Prior, high bound 95% CI	Posterior, Mean	Posterior, Low bound 95% C	Posterior, high bound 95% CI
Abundance ^a	U(100,10k) ^b	10,000	594	19,500	—	—	—
P0, Mist net	B(1,1)	0.5	0.025	0.975	0.0019	0.0016	0.0021
P0, Acoustic	B(1,1)	0.5	0.025	0.975	0.0122	0.0119	0.0125
Tree-bat effect (logit)	U(0,10)	5	0.25	9.75	1.01	1	1.02
Temp effect (logit)	N(0,3)	0	−6.21	6.19	0.31	0.29	0.33
Precip effect (logit)	N(0,3)	0	−6.18	6.2	−0.1	−0.12	−0.08
Wind effect (logit)	N(0,3)	−0.01	−6.2	6.18	−0.09	−0.11	−0.07
Prob of zero captures	B(1,1)	0.5	0.025	0.975	0.3298	0.142	0.5877
Prob of zero acoust detections	B(1,1)	0.5	0.025	0.975	0.4653	0.2579	0.6998

^a Parameters in this table reflect the base model, in which abundance was estimated separately for all species and all years (linear trend and breakpoint/white-nose syndrome models were also run). Priors for big brown bats *Eptesicus fuscus* abundance in years 2012 and 2013 were set at 1,000 to serve as a reference point for estimating abundance for other species and years.

^b For prior distributions, B(<alpha>,<beta>) refers to a Beta prior, N(<mean>,<stdev>) refers to a Gaussian prior, and U(<lower>,<upper>) refers to a uniform prior.



Table 3. Summary of bat mist net captures by year and species at New Boston Air Force Station in New Boston, New Hampshire, 2006–2013 (catch per unit effort in parentheses). Species include little brown bat *Myotis lucifugus*, northern long-eared bat *Myotis septentrionalis*, eastern small-footed bat *Myotis leibii*, big brown bat *Eptesicus fuscus*, hoary bat *Lasiurus cinereus*, and eastern red bat *Lasiurus borealis*.

Species	2006	2007	2012	2013	Total
<i>Myotis lucifugus</i>	60 (2.06)	87 (2.94)	4 (0.69)	1 (0.11)	164 (1.61)
<i>Myotis septentrionalis</i>	4 (0.14)	10 (0.34)	0	0	16 (0.16)
<i>Myotis leibii</i>	3 (0.10)	9 (0.31)	0	6 (0.70)	20 (0.20)
<i>Eptesicus fuscus</i>	42 (1.44)	50 (1.69)	20 (3.48)	20 (2.33)	142 (1.40)
<i>Lasiurus cinereus</i>	0	1 (0.03)	0	0	3 (0.03)
<i>Lasiurus borealis</i>	0	2 (0.06)	2 (0.34)	0	5 (0.05)
Total captures	109 (3.76)	159 (5.39)	26 (4.52)	27 (3.14)	350 (3.46)

those areas likely to maximize capture success (and which would become the focus of subsequent surveys).

Acoustic surveys

As with mist net data, acoustic surveys conducted in the 2002 pilot season were not considered for further analysis. A total of 18,778 calls of 8 bat species were detected in 633.8 detector-nights across 5 summer active seasons from 2010 through 2014 (Table 4; Data A3 and Data A4, *Archived Material*). *L. noctivagans* represented 3.2% of the total bat activity during the summer active season. However, it was removed from further analysis because most summer acoustic activity attributed to this species in the Northeast is actually from *E. fuscus* (Corben 2004); this assumption was reinforced by the fact that no *L. noctivagans* were captured at NBAFS despite 212 net-nights of sampling. The tricolored bat *Perimyotis subflavus* represented only 0.4% of the total bat activity. The rarity of acoustic detection and the failure to capture any individuals of this species in mist nets during the study period dictated that we also eliminated this species from further analysis. After removing these two species and rarefying the acoustic data to reduce serial correlation, the total acoustic captures were reduced to 4,689 across 6 species. Captures per unit effort peaked in 2013 at an average of 17.81 interval-detections for a standard 3-night microphone deployment period, and was lowest in 2012 at 1.32 interval-detections for a standard 3-night microphone deployment period (Table 5).

Relative abundance model

We used acoustic and mist net captures to model relative abundance for all six focal species for the period 2006 to 2014. The relative abundance of *M. lucifugus* declined significantly since 2006 (Figure 2); this decline was apparent when relative abundance for all years was modeled separately (Figure 2), when abundance was modeled as a linear trend with time (Figure 3b), and when abundance was modeled separately for the period before and after WNS was first observed at NBAFS (Figure 3a). The onset of WNS at the study site was the strongest effect size detected for the decline of *M. lucifugus*, with an estimated post-WNS decline of 75–90% of the pre-WNS abundance. There was also evidence that the abundance of *M. septentrionalis* declined since 2006 (Figure 2), but the effect of WNS was smaller, though still significant, on account of the high level of variation in the data prior to the onset of WNS (Figure 3a). There was strong evidence that the relative abundance of *M. leibii* increased since 2006 (Figure 2), with no significant impact attributed to the onset of WNS at our study site (Figure 3a). The relative abundance of *E. fuscus*, the only other focal species that hibernates in caves, showed no change in relative abundance since 2006 (Figure 2), with no significant effect from WNS (Figure 3a), nor any linear trend in abundance (Figure 3b).

The remaining two focal species (*L. borealis* and *L. cinereus*) are both migratory bats that do not hibernate in caves, and thus are not considered to be affected by WNS. Data from the model suggested that *L. borealis*

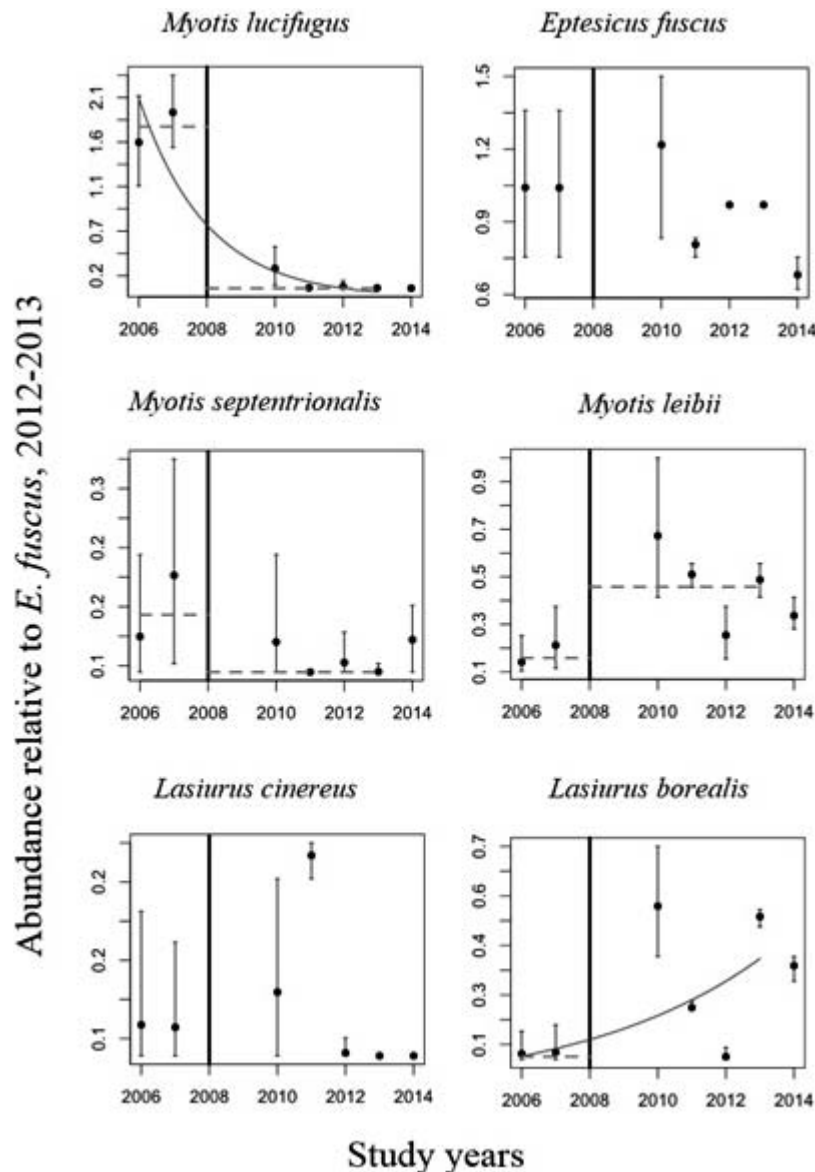
Table 4. Summary of total^a bat acoustic captures by year and species at New Boston Air Force Station in New Boston, New Hampshire, 2006–2014 (catch per unit effort in parentheses). Species include little brown bat *Myotis lucifugus*, northern long-eared bat *Myotis septentrionalis*, eastern small-footed bat *Myotis leibii*, big brown bat *Eptesicus fuscus*, hoary bat *Lasiurus cinereus*, and eastern red bat *Lasiurus borealis*.

Species	2010	2011	2012	2013	2014	Totals
<i>Myotis lucifugus</i>	10 (0.78)	62 (0.16)	1 (0.04)	39 (0.36)	4 (0.04)	116 (0.18)
<i>Myotis septentrionalis</i>	3 (0.24)	17 (0.04)	3 (0.12)	22 (0.20)	47 (0.51)	92 (0.15)
<i>Myotis leibii</i>	21 (1.64)	312 (0.78)	17 (0.68)	207 (1.92)	100 (1.09)	657 (1.04)
<i>Eptesicus fuscus</i>	46 (3.61)	595 (1.50)	0 (0.00)	926 (8.57)	241 (2.61)	1,808 (2.85)
<i>Lasiurus cinereus</i>	12 (0.94)	401 (1.01)	0 (0.00)	45 (0.42)	0 (0.00)	458 (0.72)
<i>Lasiurus borealis</i>	53 (4.16)	473 (1.19)	12 (0.48)	684 (6.33)	336 (3.65)	1,558 (2.45)
Totals	145 (11.37)	1,860 (4.70)	33 (1.32)	1,923 (17.81)	728 (7.91)	4689 (7.40)

^a Total individuals detected: raw detections were rarefied such that bats detected within 15 min of previous detections of the same species were assumed to represent the same individual.

Table 5. Summary of survey effort and total bat capture, as measured by catch per unit effort (CPUE), at New Boston Air Force Station in New Boston, New Hampshire (2006–2014).

Parameter	2006	2007	2010	2011	2012	2013	2014
Mist net survey effort (standardized 3-night sampling bout)	29	29.5	0	0	5.75	8.59	0
Total mist net captures (CPUE)	109 (3.76)	159 (5.39)	NA	NA	26 (4.52)	27 (3.14)	NA
Acoustic survey effort (detector-nights)	0	0	12.75	396	25	108	92
Total acoustic captures (CPUE)	NA	NA	145 (11.37)	1,860 (4.70)	33 (1.32)	1,923 (17.81)	728 (7.91)

**Figure 2.** Estimated relative abundances and trends for six bat species at New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, 2006–2014. All abundances were modeled relative to the abundance of big brown bats *Eptesicus fuscus* in years 2012–2013 (for which abundant and reliable data were available), and were estimated on the basis of mist net surveys (2006, 2007, 2012, 2013) and acoustic detections (2011, 2012, 2013) in a hierarchical Bayesian framework. Solid circles indicate Bayesian posterior means, and error bars indicate 95% credible intervals (CI). Log-linear trend lines are included for those species for which the 95% CI for the trend parameter did not overlap zero. Horizontal gray dashed lines denote the abundance change before and after white-nose syndrome (WNS) first affected hibernating bats in New Hampshire (2008; only depicted for those species for which the 95% CI for the WNS parameter did not overlap zero).

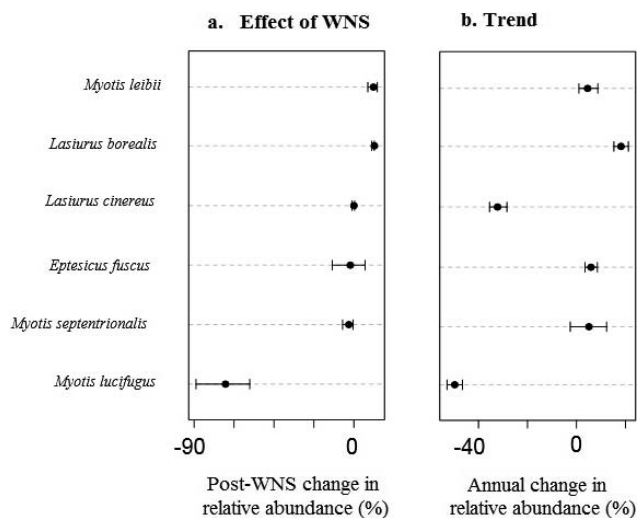


Figure 3. Systematic change in relative abundance for six bat species at New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, 2006–2014, expressed as **(a)** percent change in abundance after the appearance of white-nose syndrome (WNS; first detected in New Hampshire in 2008) and **(b)** annual percent change throughout the study period. All abundances were modeled relative to the abundance of big brown bats *Eptesicus fuscus* in years 2012–2013 (for which abundant and reliable data were available), and were estimated on the basis of mist net surveys (2006, 2007, 2012, 2013) and acoustic detections (2011, 2012, 2013) in a hierarchical Bayesian framework. Solid circles indicate Bayesian posterior means, and error bars indicate 95% credible intervals.

increased in relative abundance since 2006, based on relative abundance over the entire sampling period (Figure 2) or as a linear trend with time (Figure 3b). *L. borealis* abundance also showed a significant positive association with the onset of WNS (Figure 3a). For *L. cinereus*, there was a significant decline in abundance since 2006 based on the linear trend analysis (Figure 3b), but there was no evidence that this decline was related to the onset of WNS (Figure 3a).

Discussion

The data collected at NBAFS were primarily generated in response to the wildlife and habitat management needs of the facility and were initially focused on rare habitats and species. The initial pilot survey in 2002 was conducted to document the diversity of bat species within the NBAFS site. To conduct a comprehensive presence-absence survey, we focused our initial sampling effort to optimize the spatial variability of habitat use by bats (Hayes et al. 2009). In this initial survey, we were able to document all eight potential bat species at NBAFS based on either acoustic monitoring or mist net captures (LaGory et al. 2002). In particular, the 2002 survey made NBAFS the first site to document the presence of reproductive *M. leibii* in New Hampshire (LaGory et al. 2002). The onset of WNS at NBAFS shifted our focus toward *M. lucifugus* and *M. septentrionalis*, the

two species that appeared to be experiencing the greatest rate of decline from WNS in the Northeast (Turner et al. 2011; Langwig et al. 2012; Zalik et al. 2016). This change in management priorities also created methodological challenges as we attempted to avoid the use of mist net captures to minimize the risk of cross-contamination of bats.

The assumption of this study was that *M. lucifugus* had undergone significant decline at NBAFS since the onset of WNS. *M. lucifugus* was the dominant species captured at NBAFS when research first began in 2002. This was most likely due to the diverse foraging habitat and abundant water sources within the NBAFS. In addition to these resources, the surrounding rural landscape created abundant opportunities for maternity roosts in nearby structures. Our model showed that *M. lucifugus* abundance declined up to 90% after the onset of WNS, consistent with other studies in the region (Zalik et al. 2016). Considering that this species is one of the most abundant species across North America and is highly susceptible to WNS, *M. lucifugus* will likely continue to be the dominant host species that drives WNS across the continent (Cheng et al. 2019). However, there is evidence that *M. lucifugus* populations are persisting at a lower baseline density (Langwig et al. 2012), possibly because of pathogen tolerance or resistance (Turner et al. 2011; Frick et al. 2017). O'Regan et al. (2015) suggested that local populations of *M. lucifugus* might stabilize at these lower densities as susceptible-infected individuals are removed from the landscape, thus diminishing both the speed and extent of spread of WNS.

In contrast, *M. septentrionalis* was never abundant at NBAFS, averaging only 5.9% of the total captures during the years prior to the onset of WNS. The rarity of *M. septentrionalis* may have been due to the small amount of the preferred habitat of this species (mature interior forest habitat: Patriquin and Barclay 2003; Ford et al. 2005) within the New Boston area. Previous capture studies have shown detectable levels of decline in *M. septentrionalis* after the arrival of WNS (Hauer et al. 2016; Reynolds et al. 2016). It is likely that the low level of impact attributable to WNS reflects the poor precision of the model given the initial low abundance of *M. septentrionalis* on the landscape.

The model suggests that *M. leibii* have become more abundant at NBAFS since the onset of WNS, both as a proportion of the total bat community as well as in absolute abundance. Most of the catch per unit effort data are based on acoustic sampling, which cannot reliably be used to estimate abundance (Weller 2007); therefore, it is also possible that the higher activity level reflects a shift in habitat usage by *M. leibii* in the absence of competitors. However, the mist net catch per unit effort data suggest that *M. leibii* have become more abundant at NBAFS since WNS first appeared on the landscape. Although *M. leibii* are considered one of the hibernating species least affected by WNS (Langwig et al. 2012), previous capture studies have documented declines in *M. leibii* after the arrival of WNS (Francl et al. 2012; Moosman et al. 2013). It is unclear whether the persistence of *M. leibii* at NBAFS is due to an increase in

resources (from competitive release of the dominant species *M. lucifugus*) or the greater tolerance or resistance to WNS, as suggested by Frick et al. (2017). Data collected from NBAFS over multiple hibernation periods (Reynolds et al. 2017) suggest that *M. leibii* hibernate in Joe English Hill, and therefore this population may be persisting as a result of the presence of summer roosting and foraging habitat in close proximity to an isolated hibernaculum.

The model suggests that the *E. fuscus* population has been stable since 2006, with no detectable impact from WNS. Although *E. fuscus* are susceptible to WNS, they are considered one of the least affected hibernating species (Langwig et al. 2012). The results at NBAFS are consistent with other capture surveys that have found either no decline (Frank et al. 2014; Butchkoski and Bearer 2016) or an increase in abundance (Hauer et al. 2016) after the onset of WNS. We had assumed that the onset of WNS would have no impact on the population abundance of the two nonhibernating bat species incorporated into our model (*L. borealis* and *L. cinereus*) but the model suggests diverging trends over time for these species.

There was an apparent increase in *L. borealis* at NBAFS since 2006, in both post-WNS abundance as well as a linear increase in abundance over time. Although there is evidence of historic declines in *L. borealis* prior to 2006 (Carter et al. 2003; Winhold et al. 2008), and concern about the impact of expanding wind development on this species (Arnett et al. 2008), there was no a priori reason to assume an increasing abundance for this species over time. The positive association between *L. borealis* abundance and the presence of WNS suggests the species is benefitting from a shift in the bat community, possibly as a result of a release from competition with *M. lucifugus*. The decline in *L. cinereus* showed no association with the presence of WNS, and most likely reflects a general decline in this species, possibly due the growth of wind development across North America (Arnett et al. 2008; Rodhouse et al. 2019).

Acoustic monitoring often provides a more complete inventory of bat abundance and species diversity than mist net captures alone (Hickey and Neilson 1995; Bucci et al. 2010; Williams-Guillén and Perfecto 2011). More recently, acoustic monitoring has become an important survey tool for bat communities as the risk of spreading WNS has placed new restrictions on more invasive methods such as mist netting or hibernacula surveys (Ford et al. 2011). Acoustic surveys have also become a key component to large-scale standardized monitoring programs such as the North American Bat Monitoring Program (NABat Project: Loeb et al. 2015). But given that *Myotis* bats are the most speciose mammalian taxa globally (Morales et al. 2017), and include most of the species heavily affected by WNS, it is important to realize that myotine bats are also the most difficult to identify acoustically (Jones et al. 2004; Jennings et al. 2008; Britzke et al. 2013; Nocera et al. 2019b). The fact that automated software packages disagree on the specific identity of most files within myotine bats is the result of the high levels of intrinsic variation in call structure that exists at multiple interacting levels (Russo et al. 2018;

Nocera et al. 2019b). This is compounded by the fact that each software package relies upon different spectral and temporal features of a call for identification and uses unique reference call libraries (Clement et al. 2014).

The present study relied on EchoClass as the primary file classifier. We chose not to use a second software package to validate the species identification because this approach is not productive for individual files. Previous analysis of data from NBAFS suggested that the overall file-level congruence between EchoClass and BCID East (Bat Call Identification, Kansas City, MO) was only 26% (Reynolds 2016), similar to the level of congruence documented for these same two software packages by Lemen et al. (2015). Therefore, we chose to utilize a semiquantitative approach for each file using the call parameters generated by the software. This approach (classifying files based on the dominant call assignments) is consistent with how automated software packages develop their Discriminant Functions Analyses criteria in general and complements the conservative nature of EchoClass in particular (Lemen et al. 2015; Nocera et al. 2019b). The common capture-per-unit-effort parameter we developed standardized the sampling effort between mist netting and acoustic monitoring in terms of both duration and sampling area. We also attempted to control for many of the uncertainties that come with acoustic sampling, including serial correlation and detection bias between species. Although these features may require further refinement, the success of this model in deriving outcomes that are consistent with regional studies that rely on either mist net sampling (Moosman et al. 2013) or acoustic monitoring (Brooks 2011) suggest that these parameterizations are valid and constructive. Therefore, we feel that this methodology will prove to be both conservative in design and robust to different data sets.

Like other researchers (Lemen et al. 2015; Russo and Voigt 2016), we urge caution when designing acoustic surveys and analyzing the data to determine the presence of rare species. Researchers should have a clear understanding of the capabilities and limitations of both the equipment and the analysis software (Kubista and Bruckner 2017), and understand the intrinsic potential for misidentification of species, either from manual review or through automated software packages. Given these caveats, however, numerous studies have shown that the common acoustic detectors and automated software packages generally have a high level of agreement when determining the presence of species across a survey period (Nocera et al. 2019b). The use of relative abundance models and occupancy models to generate robust estimates of population abundance will also overcome one of the primary limitations of acoustic surveys. The potential value of acoustic surveys to generate baseline data for the long-term monitoring of species at risk, as well as document shifts in community composition over time, justify continued work toward resolving these caveats.

Long-term studies using standardized monitoring methods have proven critical for documenting declines in animal populations such as amphibians (Blaustein et

al. 1994), birds (Roth and Johnson 1993; Le Gouar et al. 2011), and mammals (Durant et al. 2007), including bats (Frick et al. 2010). But often conservation and management decisions must be made in the absence of such data. In these cases, resource managers will need to be able to integrate existing data with ongoing research to quantify changes in species abundance or community composition. The NBAFS site represented a typical situation where multiple short-term projects were conducted using diverse sampling techniques. When the focus of this research shifted from rare species management to documenting a dramatic shift in community composition due to an emergent disease, a tool was needed to quantify these changes. This model represents a first attempt to develop a tool that can compare relatively disparate data sets using a common sampling metric, to quantify changes in species abundance and community composition.

Long-term data are crucial for understanding the disease ecology of social mammals (Smith et al. 2017). This is particularly true for diseases such as WNS that encompass multiple scales of interacting biotic and environmental factors (Crowl et al. 2008). The processes that affect iteroparous species can take multiple years or even decades to become evident (Clutton-Brock and Sheldon 2010), so it is critical to have baseline population data to detect population trends. This is particularly true for disease ecology when the host is a highly social and mobile species such as *M. lucifugus* (Langwig et al. 2015). Given the speed and extent of the spread of WNS, statistical techniques that can incorporate existing survey data into relative abundance estimates may be the best way to generate the baseline data needed to inform conservation and management decisions. It is our hope that such a Bayesian approach can be used to conduct meta-analyses on diverse data sets across a broad geographic range so that we can understand and respond to the impacts of WNS as it extends across the continent.

This model also could generate a wealth of information that is relevant to both research and conservation management goals that extend beyond disease ecology. For example, wind development projects often incorporate similar survey techniques (mist netting and acoustic monitoring) to evaluate potential risk prior to construction, and then rely on different survey techniques (acoustic monitoring and carcass surveys) to evaluate effect on bats postconstruction. A model that could standardize sampling effort and monitoring for changes in the community composition would provide a significant management resource. This model could also be applied to development projects that occur within the geographic range of federally listed species (such as *Myotis sodalis* and *M. septentrionalis*), where federal regulators often recommend both acoustic and mist net sampling to determine presence (USFWS 2019), but do not provide a method of integrating these data into measures of population abundance. As development pressures and climate change continue to have an impact on natural resources, it will be increasingly important to use ecological indicators such as bats to

track environmental change and ecosystem health (Tuneu-Corral et al. 2020).

Supplemental Material

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Reference S1. Clawson RL. 2001. Efficacy of Anabat detectors to investigate the abundance and diversity of Missouri's bat fauna, with emphasis on the endangered Indiana bat (*Myotis sodalis*). Federal Aid Project Number W-13-R-55. Springfield, Virginia: Missouri Department of Conservation.

Available: <https://doi.org/10.3996/JFWM-20-043.S1> (2.5 MB PDF)

Reference S2. LaGory KE, Reynolds DS, Kuiper JA. 2002. A survey of the bats of New Boston Air Force Station, New Hampshire. Report of Environmental Assessment Division, Argonne National Laboratory, Chicago, Illinois.

Available: <https://doi.org/10.3996/JFWM-20-043.S2> (4.97 MB PDF)

Reference S3. Loeb SC, Rodhouse TJ, Ellison LE, Lausen CL, Reichard JD, Irvine KM, Ingersoll TE, Coleman JTH, Thogmartin WE, Sauer JR, Francis CM, Bayless ML, Stanley TR, Johnson DH. 2015. A plan for the North American Bat Monitoring Program (NABat). Asheville, North Carolina: U.S. Department of Agriculture Forest Service, Southern Research Station. General Technical Report SRS-208.

Available: <https://doi.org/10.3996/JFWM-20-043.S3> (7.34 MB PDF)

Reference S4. Reynolds DS. 2016. Acoustic bat survey of New Boston Air Force Station (NBAFS), Summer 2016. Report to U.S. Fish and Wildlife Service, Concord, New Hampshire.

Available: <https://doi.org/10.3996/JFWM-20-043.S4> (2.42 MB DOCX)

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Data A1. Acoustic bat detection records from New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, between 30 July 2002 and 30 September



2014. Each row represents a unique detection event, and columns represent the site of deployment, unique file identification code, date, time, and species. Note that we used the SPECIES 2 column in the analyses presented herein.

Available: <https://doi.org/10.3996/JFWM-20-043.S5> (2.23 MB CSV)

Data A2. Acoustic monitoring efforts from New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, between 21 June 2002 and 1 January 2014. Each row represents a single microphone deployment and columns represent the initial deployment date, length of deployment in hours, site id, location information (LAT and LONG in decimal degrees). Additional columns record site-level covariates: distance to nearest pond (PONDm), distance to known hibernaculum (HILLm) and a categorical habitat variable (HABITAT). Bat detection records: each row represents a unique detection event, and columns represent the site of deployment, unique file identification code, date, time, and species. Note that we used the SPECIES 2 column in the analyses presented herein.

Available: <https://doi.org/10.3996/JFWM-20-043.S6> (4 KB CSV)

Data A3. Bat capture records based on mist net sampling from New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, between 9 July 1995 and 20 June 2013. Each row represents a unique capture event, and columns represent the date and time of capture, a unique deployment code (NET CODE), species, sex, reproductive status, and a boolean indicator of whether or not the individual had been captured previously (RECAPT). Bat detection records: each row represents a unique detection event, and columns represent the site of deployment, unique file identification code, date, time, and species. Note that we used the SPECIES 2 column in the analyses presented herein.

Available: <https://doi.org/10.3996/JFWM-20-043.S7> (12 KB CSV)

Data A4. Mist net survey effort from New Boston Air Force Station (NBAFS) in New Boston, New Hampshire, between 9 July 1995 and 18 June 2013. Each row represents a single mist net deployment and columns represent the initial deployment date (First Night), length of deployment in number of nights (NIGHTS), unique net deployment identification number (NET), net height and size, and location information (LAT and LONG in decimal degrees). Additional columns record site-level covariates: distance to nearest pond (PONDm), distance to known hibernaculum (HILLm), and a categorical habitat variable (HABITAT). Bat detection records: each row represents a unique detection event, and columns represent the site of deployment, unique file identification code, date, time, and species. Note that we used the SPECIES 2 column in the analyses presented herein.

Available: <https://doi.org/10.3996/JFWM-20-043.S8> (10 KB CSV)

Data A5. Weather Variables recorded at the National Weather Service Weather Station in Manchester, New Hampshire. This file was obtained from the National Weather Service and contains daily average weather variables recorded at the National Weather Service weather station located at the Manchester Airport (MHT). Each row represents a unique day between 1 January 2000 and 31 January 2014 and each column represents standard National Weather Service variables including precipitation (mm), temperature (in C, min, max and mean), and wind speed (mps). Missing data are represented as 9999.

Available: <https://doi.org/10.3996/JFWM-20-043.S9> (556 KB CSV)

Text A1. R Coding File. This file contains the R code for inferring population trajectories for the community of bats occupying New Boston Air Force Station (NBAFS) based on mist net capture and acoustic detection data collected between 9 July 1995 and 30 September 2014. This R Coding file was also used to generate the results and figures presented herein.

Available: <https://doi.org/10.3996/JFWM-20-043.S10> (83 KB R)

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Any use of trade, product, website, or firm names in this publication is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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