

Title:

A field observation method to characterize site soundscape and improve detection probability estimation for eastern bat species in North America

Authors and affiliations:

Daniel Peacock¹, Sihao Chen², Jorge Rivera³, Kevin A. Parker⁴, Katherine Caldwell-Etchison⁵,
Matina C. Kalcounis-Rueppell⁶, and Han Li^{1,*}

¹ Department of Biology, University of Nebraska Omaha, Omaha, Nebraska, United States

² Department of Landscape Architecture, College of Horticulture and Landscape Architecture,
Southwest University, Chongqing, China

³ Department of Electrical and Computer Engineering, University of Nebraska Lincoln, Lincoln,
Nebraska, United States

⁴ Parker Ecology, LLC., Juneau, Alaska, United States

⁵ North Carolina Wildlife Resources Commission, Asheville, North Carolina, United States

⁶ Department of Biology, University of Alberta, Edmonton, Canada

*Corresponding author: Han Li, hanli@unomaha.edu, ORCID: 0000-0002-3627-5941

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Abstract

Acoustic monitoring of bat activity has become increasingly prevalent in recent years. A major challenge is imperfect detection caused by bat behavior and the physical soundscape. Although environmental factors such as weather are commonly considered to account for imperfect detection, there is a lack of an easy-to-use, widely applicable protocol for characterizing soundscapes. We introduce a field-based observation method requiring minimal training to characterize the soundscape. Results from two case studies demonstrate that, in both temperate forest and grassland ecosystems, our soundscape measures better explained imperfect detection than weather conditions for eastern bat species in North America. We emphasize that soundscape characteristics should be considered when selecting acoustic monitoring sites and incorporated into quantitative analyses of ecological processes.

Key words

Bats, detection probability, forest, grassland, hierarchical occupancy models, NABat, North America, passive acoustic monitoring, soundscape

Practitioner Points

- When choosing acoustic monitoring sites, practitioners should consider canopy cover, physical structure, and proximity to water bodies at the site scale for their target species.
- When analyzing acoustic data, site soundscapes may cause species to go undetected; quantitative assessment of false absences is necessary before making conservation and management decisions.
- Practitioners may need to modify acoustic monitoring protocols between grassland and forest ecosystems, even when monitoring the same bat species.

Introduction

In the past few decades, our ability to monitor bats has improved significantly, propelled by the technological development of acoustic recording devices and coordinated broad scale monitoring programs (Geng et al., 2026; Raad et al., 2026; Reichert et al., 2021). Acoustic monitoring of bat flight activities, undoubtedly with its own limitations, may simultaneously collect information on multiple species of bats, and yield presence, activity level, and behavior data. Such tools have been proven cost-effective and allow biologists to investigate ecological questions at unprecedented spatial scales (Li and Kalcounis-Rueppell, 2018; Neece et al., 2019; Rodhouse et al., 2012). Amongst all possible ways to use bat acoustic data for scientific investigation, a common quantitative tool to accompany bat acoustic monitoring is occupancy modeling (Neece et al., 2018; Rodhouse et al., 2019; Udell et al., 2025).

Occupancy models are a type of multilevel hierarchical model first introduced in early 2000s to process presence/non-presence animal data with the capacity to handle imperfect detections from the field data collection (Goldstein et al., 2024; MacKenzie and Kendall, 2002; Tyre et al., 2003). Imperfect detections of animals in the field may arise due to animals being naturally inconspicuous, altered animal behaviors related to the ambient conditions, and physical limitations of observers (MacKenzie et al., 2017). Almost all bat species in the United States and Canada are nocturnal, small in size, and able to fly, making them less conspicuous than many other animals. Bats change behaviors with physical habitat, temperature, wind, and moonlight (Kalcounis et al., 1999; Li et al., 2020; Negraeff and Brigham, 1995). The acoustic observation methods are governed by physical laws in terms of how sound travels and is received and recorded (Russo and Voigt, 2016). Therefore, multiple factors can contribute to imperfect detections and should be considered when constructing occupancy models to analyze bat acoustic data.

Bat flight and acoustic activity is affected by weather. Thus temperature, air pressure, humidity, and wind speed are commonly considered when modeling imperfect detections (Burns et al., 2019; Neece et al., 2018; Starbuck et al., 2015; Udell et al., 2025). Notably, Udell et al. (2025) considered not only linear but also quadratic effects of weather variables when modeling detection probability. Researchers may use ordinal date as the proxy or supplement for weather variables (Hein et al., 2009; Pauli et al., 2017; Smith et al., 2021). An additional advantage of ordinal date is that it can account for life history events in bats (such as pups becoming volant) that might affect acoustic detection (Rodhouse et al., 2015). In addition to weather variables, researchers include moon phase or moon illumination to improve detection estimation (Blakey et al., 2019; Blanco and Garrie, 2020) because bats change flight behaviors in response to moon phase (Li et al., 2024).

Less consideration has been given to the physical soundscape that may cause imperfect detection. When sound propagates through air, physical obstructions such as vegetation and humanmade structures reflect, absorb, and scatter ultrasonic signals, reducing their energy before they reach a receiver or the microphone. Thus, bat detection is affected by clutter in the immediate surrounding of a recording site and how the microphone of the recording device is placed (Adams et al., 2012; Li and Wilkins, 2022; Loeb et al., 2020; O'Keefe et al., 2014). One

typical soundscape measure is a clutter estimate (Bender et al., 2015; Neece et al., 2018; Perea et al., 2024; Smith et al., 2021). Various methods are used to generate clutter estimates, including extraction of land cover maps via GIS tools (Smith et al., 2021), field observations and estimations (Neece et al., 2018), and using a vegetation profile board in the field (Bender et al., 2015; Nudds, 1977; Perea et al., 2024). In addition, research with forestry components include basal area and other tree measurements to characterize the trees as clutter (Bender et al., 2015; Perea et al., 2024; Starbuck et al., 2015). A variety of site soundscape estimation methods currently exist, yet no standardized protocol has been broadly adopted. This lack of standard protocols complicates comparisons across studies and limits the scalability of bat monitoring efforts.

Therefore, there is a need for an easy-to-use and widely applicable protocol for characterizing the soundscape to improve the estimation of imperfect detection of bats for occupancy models. First, current broad-scale coordinated bat acoustic monitoring, such as the North American Bat Monitoring Program (NABat) may involve many different types of professionals including game wardens, law enforcements officials, and park service employees as well as citizen and community scientists to deploy recording devices (Border et al., 2017; Gili et al., 2024; Reichert et al., 2021). These participants may have different skills and access to equipment for implementing protocols for characterizing the bat recording site soundscape. A simple protocol involving commonly owned technology (e.g., a mobile phone with camera) can facilitate participation. Second, beyond forest ecosystems, vegetation structures change and objects that can potentially affect how the sound propagates may not be trees (Raad et al., 2026). For example, in urban environments, fences, buildings, and yard decor may form spatial clutter (Li and Wilkins, 2022). Furthermore, water, and especially open water surfaces may alter sound reflection (Russo et al, 2012). Thus, there is the need for a protocol that is applicable to many different environments, not just forests. Lastly, besides GIS maps, there are no raw records generated by other reported methods to document soundscape. Such archived raw records can be valuable for future re-evaluation of the soundscape of a bat monitoring site and improve data shareability and reusability. To address these gaps, we introduce a simple field observation method that requires minimal training to describe the soundscape. We used two case studies to demonstrate its effectiveness to improve detection probability for eastern bat species in North America.

Methods

Soundscape characterization protocol

At any given site, the position of the bat detector fixation should be used for observation and soundscape characterization. The observer should stand as close to the microphone as possible during the process and a camera is needed to photograph the observations.

1. Water facing – the observer examines the direction where the microphone is facing (if the microphone is tilted to face up or down, observe the direction parallel to the ground instead of the tilted direction), determine within the visual range if waterbodies are

present and record as a binary answer (yes/no). The waterbody can be either permanent or ephemeral (e.g., a puddle after a rainstorm).

2. Site canopy cover – the observer looks 90 degrees up and examines the canopy cover above the detector microphone within the visible range. The observer does not need to turn their head or body to increase the observation range. Based on what they see, they estimate canopy cover as one of the following:
 - a. Open – less than one third of the sky is covered
 - b. Half – about one third to two thirds of the sky is covered
 - c. Closed – more than two thirds of the sky is covered
3. Site structure – the observer looks at the surroundings of the detector placement, and chooses the one of the following that best describes the immediate surrounding (within 25 meter radius for 360 degrees):
 - a. Field – no tree or only scattered trees or other tall structures in the immediate surrounding
 - b. Edge – no trees or only scant trees on one half with the other half forming a complete vertical boundary by the trees with some small gaps allowable
 - c. Corridor – a clear path for humans, animals, or water through the middle and trees forming relatively complete vertical boundaries with some allowable small gaps on either side. The path should not be wider than 5 times that of the vertical height of the vegetation nor narrower than one third of the vertical height of the vegetation.
 - d. Interior – no clear path or a very narrow path for humans, animals, or water narrower than one third of the vertical height of vegetation.

When photos are taken, at least three are needed. The camera should be placed approximately 1.6 -- 1.8 meters above ground which equates the approximate height of an average person. For the first photo, the camera lens should face the direction where the microphone is facing. This photo will provide information on water presence. For the second photo, the camera should be placed with the lens facing 90 degrees up. This photo will capture the canopy cover information. The third photo can be taken as a panorama photo to capture the immediate surroundings of the bat detector. Alternatively, a series of photos can be taken to capture the panorama.

Case study 1 – NABat stationary point survey in North Carolina

From 2015 to 2022, in June and July, we conducted statewide NABat stationary point survey (Loeb et al., 2015; Neece et al., 2018) in North Carolina, USA (Fig. 1a). North Carolina represents typical temperate forest ecosystems in North America (Chen and Li, 2025). To select field sites, we overlaid the NABat grid cell map with national land cover database (NLCD) land cover map (Yang et al., 2018) and the North Carolina public land map. Within an NABat grid cell, we considered both land cover heterogeneity and site accessibility (public lands or private lands with landowners' permits) to choose 2–4 sites for acoustic monitoring. These sites within a grid cell represented the most common land cover types. During the initial site selection process in 2015, there was no consideration of soundscape. From 2016 onwards, we started taking photos

as per the protocol described above to characterize each site's soundscape (see site canopy examples in Fig. 1c-1e).

At each site, we placed an AnaBat SD2 bat detector (Titley Scientific Inc., Australia) approximately 1.7 – 2.7 meters above the ground with the detector microphone facing a random direction as long as there was no object that could directly block sound within 10 meters. The detailed detector acoustic setting was described by Li and Kalcounis-Rueppell (2018). The field site selection and detector setup occurred during the day. Each detector recorded for four consecutive nights, independent of weather conditions, from sunset to sunrise. Only sites with four complete nights of recordings were included in the analysis for this case study. For each site during monitoring, nightly weather data (daily maximum and minimum temperatures and precipitation) were manually recorded from a variety of common weather forecast websites based on each site's coordinates. We also supplemented weather data from the National Oceanic and Atmospheric Administration historical weather using records from the nearest weather station when manual entries were missing (Parker et al., 2020).

We monitored 8–10 sites concurrently, representing 2–3 NABat grid cells. After four nights of monitoring, we moved the bat detectors to the next group of sites. Within a field season year, we monitored approximately 80–100 sites representing 30–40 NABat grid cells. Across years, when previously selected sites became unavailable due to various reasons (e.g., land ownership changes, natural disasters, etc.), new sites were selected as replacements to represent similar land cover within the grid cell. In total, 187 sites were surveyed across all years and 151 of these were surveyed over multiple years. Before each field season, bat detectors and microphones were calibrated using the Anabat Equalizer (Titley Scientific Inc., Australia, Li and Kalcounis-Rueppell, 2018; Neece et al., 2019).

We processed all recordings first following the automatic species identification protocol described by Parker et al. (2019) using Kaleidoscope (version 4.5, Wildlife Acoustics Inc, Maynard, MA, United States). After the automatic species identification, the last author manually vetted recordings to generate the presence/no detection dataset. We constructed multi-season single species dynamics occupancy models with this dataset (MacKenzie et al., 2017) using R package “unmarked” (Fiske et al., 2017). Among 17 bat species present in North Carolina, we constructed occupancy models for eight species with a known statewide distribution using all sites [big brown (*Eptesicus fuscus*), eastern red (*Lasiurus borealis*), hoary (*Lasiurus cinereus*), silver-haired (*Lasionycteris noctivagans*), little brown (*Myotis lucifugus*), evening (*Nycticeius humeralis*), tricolored (*Perimyotis subflavus*), Mexican free-tailed bats (*Tadarida brasiliensis*)] and three species with limited distributions using sites only from specific regions [southeastern myotis (*Myotis austroriparius*) – coastal region sites only; northern long-eared bat (*Myotis septentrionalis*) – coastal and mountain region sites only; gray bat (*Myotis grisescens*), mountain region sites only, Etchison and Weber, 2020; Li et al., 2024).

In this case study, we only reported the detection probability estimation results generated by models with occupancy, extinction, and colonization formulae including only a constant. To estimate detection probability, we considered the typical weather observation covariates: daily maximum and minimum temperature (°C), precipitation (mm). Additionally, we extracted moon

phase following protocols described by Li et al. (2024). As the original site selection was conducted using a land cover map, we also extracted two land cover covariates. Both covariates were extracted from the NLCD maps at the 9-pixel scale, the 30m by 30m pixel where the site was located and its eight immediate neighbors. The first covariate called ‘GIS water’ measured how many pixels out of 9 were water, including both water and herbaceous wetland. The second covariate called ‘GIS vegetation’ measured how many pixels out of 9 were tree based vegetation, including all three types of forests and woody wetland. These six covariates along with the three soundscape covariates were used to estimate detection probability. When constructing occupancy models, we included one covariate per model and ranked these single-variate models and the null model by Akaike Information Criterion (AIC) to examine if these soundscape covariates would perform better than weather and GIS covariates. When adding a covariate reduced the null model AIC by 2 or more, the covariate was included for the multivariate detection probability estimation. Multicollinearity was checked among selected detection probability covariates following the protocol in Li et al. (2019) prior to developing multivariate detection probability models. The final model, either single-variate or multivariate with the lowest AIC for each species was used for visualizing the covariates’ effects on the detection probability. The final detection probability model for each species is reported in Supplementary Materials 1 and used for other studies.

Case study 2 – post white-nose syndrome baseline bat monitoring in Nebraska

In 2024, we conducted acoustic bat monitoring in eastern and central Nebraska, a region historically dominated by tallgrass and mixed-grass prairies and altered by agricultural and urban land conversion in recent centuries (Hanberry, 2025). Between June and August 2024, we collected recordings from 113 sites (Fig. 2a). Among these sites, 72 of them were previously monitored between 2012 and 2014 prior to the arrival of the white-nose syndrome in the region (White et al., 2016). From 2012 to 2014 monitoring, sites were selected opportunistically based on existing habitat knowledge. More recently in 2024, 41 new sites were selected to replace previously monitored sites that had become inaccessible or to fill in large spatial gaps between previously existing sites. To ensure site independence and capture land cover diversity, 106 sites were at least 3 km away from any other sites and all sites were at least 1 km away from any other site. All sites were photographed following the soundscape characterization protocol described above and classified by the first author. We used this dataset to test whether our protocol might improve the estimation of bat detection probability in grassland ecosystems. As the site selection in this case study was based on previous research, we did not extract GIS derived covariates like in case study 1.

At each site, we used the Song Meter Mini Bat or Song Meter Mini Bat 2 (Wildlife Acoustics Inc, Maynard, MA, United States) to record bat calls. The difference between the two detector models was the battery capacity and the weatherproof design, with the same ultrasonic microphones in both models (<https://www.wildlifeacoustics.com/products/song-meter-mini-2-aa>). The bat detector was secured to an object that was already present at the site, such as a tree, a bridge column, or a traffic signpost, 1.5 – 2 meters above the ground. The bat detector’s microphone was oriented towards a direction without clutter. The monitoring scheme followed

the NABat stationary point survey protocol to record bat acoustic activities from sunset to sunrise for four consecutive nights. Detectors were set to record in full-spectrum format with a sampling rate of 256 kHz, a minimum trigger frequency of 16 kHz, a maximum recording length of 15 seconds, and a trigger window of 3 seconds. Site coordinates were recorded using the Wildlife Acoustics Configurator app paired with the GPS function of a mobile phone. These coordinates were used to extract weather covariates, including daily minimum and maximum temperature (°C), total overnight precipitation (mm), and lunar illumination. Temperature and precipitation was extracted using R package ‘openmeteo’ (Pisel, 2023). Lunar illumination was extracted using the R package ‘moonlit’ (Śmielak, 2023).

All acoustic recordings were processed following the same acoustic analysis protocol described in case study 1. The candidate species considered for automatic identification in Kaleidoscope were big brown (*Eptesicus fuscus*), eastern red (*Lasiurus borealis*), hoary (*Lasiurus cinereus*), silver-haired (*Lasionycteris noctivagans*), little brown (*Myotis lucifugus*), northern long-eared bat (*Myotis septentrionalis*), evening (*Nycticeius humeralis*), tricolored (*Perimyotis subflavus*), Mexican free-tailed bats (*Tadarida brasiliensis*). The first author conducted manual verification to generate site level presence/no detection data. Compared to case study 1, the case study 2 location has fewer bat species and is considered as the species distribution range periphery for multiple species with most sites dominated by the big brown bat (Raad et al., 2026). We constructed single-season single-species occupancy models for four species: the hoary bat, silver-haired bat, evening bat, and tricolored bat. We followed the same model selection process described in case study 1 to test if soundscape covariates would perform better than weather covariates in the grassland ecosystem. The final model, either single-variate or multivariate with the lowest AIC for each species was reported and used for visualizing the covariates’ effects on the detection probability. The final detection probability model for each species is reported in Supplementary Materials 1 and used for other studies.

Results

Case study 1

All 11 species examined in this case study, except for the evening bat, had one of the soundscape covariates as the top detection probability model (Fig 3a, Supplementary Materials 1). The ‘site canopy’ was the top single-variate model for seven species. The big brown bat, eastern red bat, hoary bat, silver-haired bat, and Mexican free-tailed bat all had significantly higher detection probabilities with ‘open canopy’, whereas the southeastern myotis bat and northern long-eared bat had highest detection probabilities with ‘closed canopy’ (Fig 4). For the gray bat and little brown bat, site structure was the top single-variate model. The structure ‘field’ had significantly lower detection probability than other site structures for the gray bat (Fig 4). Both ‘field’ and ‘interior’ had lower detection probability than ‘edge’ and ‘corridor’ for the little brown bat (Fig 4). For the tricolored bat, detection probability was significantly higher at ‘water facing’ sites than sites than ‘not facing water’. For the evening bat, GIS derived ‘water cover’ near the site was the top model, showing increased detection probability with increased ‘water cover’ (Fig 4).

Besides the top model, all species had other covariates that improved detection probability estimation than the null model (Fig 3a). Besides the evening bat, all other species had other soundscape covariates that could improve detection probability estimation. Interestingly, for seven species (big brown, hoary, silver-haired, southeastern myotis, gray, northern long-eared bat), weather covariates did not improve detection probability estimation from the null model. Moon phase was only significant for the tricolored bat detection probability and had no effect on other species' detection probability (Fig 3a). Similar to weather covariates, GIS derived covariates only had limited impacts on detection probability estimation. Besides the evening bat, GIS derived vegetation improved detection probability estimation for the big brown and eastern red bat.

Case study 2

In the grassland ecosystem, two out of four species had 'site structure' as the top single-variate detection probability model (Fig 3b). For the tricolored bat, 'site structure' was the only covariate that improved detection probability estimation from the null model. 'Edge' and 'interior sites' had higher detection probability than other two site structures (Fig 5). Site structure was the only covariate that improved detection probability estimation from the null model (Fig 3b). For the hoary bat, 'edge' had significantly higher detection probability than other site structures (Fig 5). Temperature covariates improved the hoary bat detection probability estimation (Fig 3b). As in case study 1, 'daily max temperature' was the only covariate that improved detection probability estimation for the evening bat. The evening bat had higher detection probability on warmer nights (Fig 5). Interestingly, none of the covariates improved the silver-haired bat detection probability in the grassland.

Discussion

Both case studies demonstrate that our soundscape characterization protocol can improve bat acoustic detection probability estimation and outperform typical weather variables for most species in two different ecosystems. The effectiveness of soundscape measures reflects the nature of acoustic monitoring where basic bat biology and physics of sound are intertwined. When using echolocation calls to monitor and identify bat species, it is essential that the recordings are of high quality (Russo and Voigt, 2016). Therefore, it is not surprising that relatively open environments without clutter distorting sound propagation yield the highest quality of recordings, which then allows for more confident species identification. For species that fly through open areas frequently, sites with an open structure or open canopy will have a higher chance to detect them. In contrast, northern long-eared bats and other myotis species are known to be active in cluttered spaces (Loeb et al., 2026; Veum et al., 2025). Biologically these species may avoid open soundscapes. Therefore, detection probability estimations for these species reflect how they select microhabitats.

The variation in detection probability across different soundscapes further implies that the detector's location selection in the microhabitat is important. For example, when monitoring a managed timber production forest where endangered myotis species may reside, a recent clear-cut open area as a monitoring site may not be suitable for effectively detecting the targeted

species. Similarly, placing bat detectors in a dense forest through a completely random site selection process will not be effective for monitoring hoary or Mexican free-tailed bats as open adapted species may not be capable of flying through cluttered space (Jenkins et al., 2026; Li and Wilkins, 2022). When different soundscape options are available, detection site selection should balance the consideration of recording quality and the species' biology. The monitoring goal should also be considered carefully. If the goal is to document the biodiversity of bats, multiple sites with complementing soundscapes should be monitored.

Currently our knowledge about bat movements at the local fine scale (e.g., within 500m to 1km of a day or night roost) is limited, which hinders our ability to choose acoustic sites more effectively. For species like the northern long-eared bat, there is almost no information describing its movement. It is not clear whether or how often this species flies through open areas, and whether such movement patterns vary across different ecoregions. The lack of knowledge is likely due to the drastic decline in population since the outbreak of the white-nose syndrome and the lack of suitable tracking tools before this species' decline. One important future research direction is better understanding different species movements with precise fine resolution tracking tools. For example, newly developed ratio transmitters may adopt low-bandwidth cellular standards and use commercial cellular networks to upload localizations (Toledo, 2025), allowing more effective tracking. Additionally, we underscore the need to study the basic biology of common species, including their movement ecology to form the knowledge foundation to prepare for unexpected declines (Münzer et al., 2023; Russo and Dechmann, 2025)

Even though weather conditions have been documented to affect bat acoustic activity in the study areas for both cases (Li et al., 2020, 2019; Li and White, 2024) and commonly considered for detection probability estimation, our results showed that they were ineffective for many species in detection probability estimation. One possible explanation is weather data precision and quality. Weather data obtained from commercial weather forecasts might not accurately describe the weather condition at a specific site. Usually, the weather information may be generated from models or from the nearest weather station. For remote sites without a nearby weather station or sites in mountainous regions where elevation and aspect alters weather within a short distance, weather loggers may be necessary to yield precise and accurate data for statistical analysis. Additionally, ineffectiveness may be related to limitations of the occupancy modeling technique where animal activity level is reduced to presence or no detection. Therefore, environmental variables that affect bat activity might not affect presence. For example, bats usually do not fly out of their roosts when it is raining. However, bats can leave the roost between bouts of rain and still be recorded by detectors. Similarly, moon illumination may alter bat activity level and reduce certain species activity (Li et al., 2024). Both reduced and normal levels of acoustic activity over one night will yield the same presence data point in commonly used occupancy models unless multistate occupancy models are used (Steen et al., 2023).

When comparing the results between two ecosystems, we did not find consistency. Even though soundscape variables in both cases generally outperformed other variables in detection probability estimation, the most informative variable varied between cases for the same species.

Undoubtedly the physical environment varies significantly, featuring more openness and fewer trees in the grassland ecosystem (Raad et al., 2026). Such differences may explain why certain physical structures such as forest-open edges concentrate bats in the grassland and why species like the hoary bat would have the highest detection probability at edge sites. It is also important to note context dependency in ecological processes (Oldfather et al., 2020; Raad et al., 2026). For example, the same species may use different structures to roost in different regions (Münzer et al., 2023; Wilkins, 1989). Population densities may also differ, which in turn leads to differing competition for the same resource. Thus, the soundscape preference of the same species is expected to vary between ecoregions. Our results on detection probability adds another piece of evidence that region-specific bat acoustic monitoring protocols are needed.

Currently our soundscape characterization protocol only yields qualitative variables for analysis. However, it has the potential to yield quantitative variables for more precise analysis. The photos collected during the observation can be quantitatively analyzed, even in a retroactive manner for archived data. For example, more and more tools have been developed to analyze smartphone photos to estimate canopy cover (Chianucci et al., 2022; Yin et al., 2022). Similarly, LiDAR equipped smartphones have been proven useful for scanning and generating 3-D information of objects (Costantino et al., 2022; Tavani et al., 2022). Such technology has been applied to vegetation surveys for estimating tree diameter and other important measures that contribute to spatial clutter (Gülci et al., 2023; Tatsumi et al., 2023; Xuan et al., 2025). Even though testing the tools described here is beyond the scope of our study, integrating these tools into our soundscape characterization protocol in the near future is a priority.

In conclusion, we presented a simple field observation based protocol to characterize recording site soundscape. Variables generated from the protocol improved detection probability estimation for bats in two different ecosystems, which ultimately allows for more accurate occupancy estimation. Researchers should consider soundscape measurements when collecting bat acoustic data to incorporate microhabitat selection into analysis of other ecological processes. Our results also provide insights on how to choose suitable sites if targeting certain species. Lastly, we underscore the need for more studies of bat movement behaviors because the foundation of bat bioacoustics' is predicated on the physics of sound and the biology of bats.

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Ethics Statement

Passive acoustic monitoring of bats is exempted from ethical approval in both states where the fieldwork was conducted.

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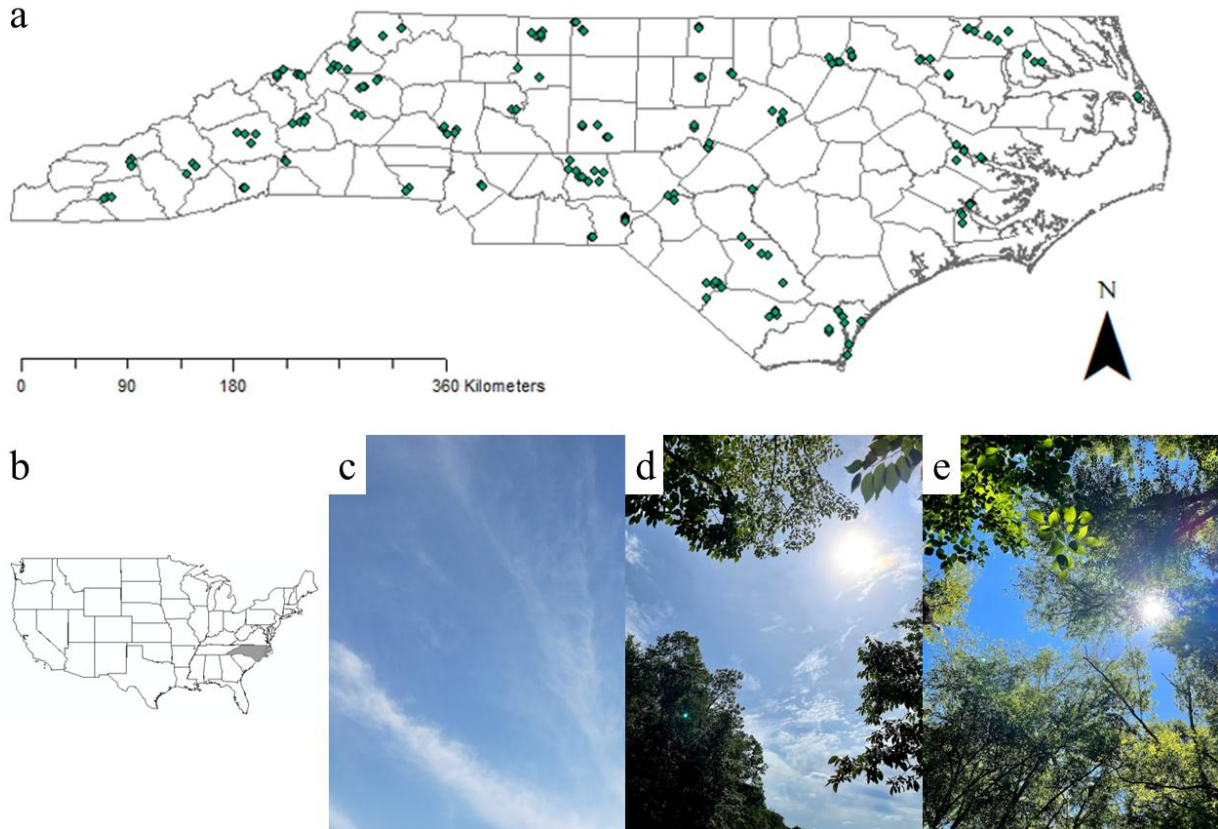
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587 **Figures and figure captions**



588

589 Fig. 1 Case 1 bat acoustic monitoring sites in North Carolina (a) and the state's location in the
590 United States (b), representing the temperate forest ecosystem. North American Bat Monitoring
591 Program stationary point survey was conducted at these sites from 2015-2022 and site
592 soundscape was characterized. Examples of site canopy observation photos show open (c),
593 intermediate (d), and closed (e) based on the soundscape characterization protocol.

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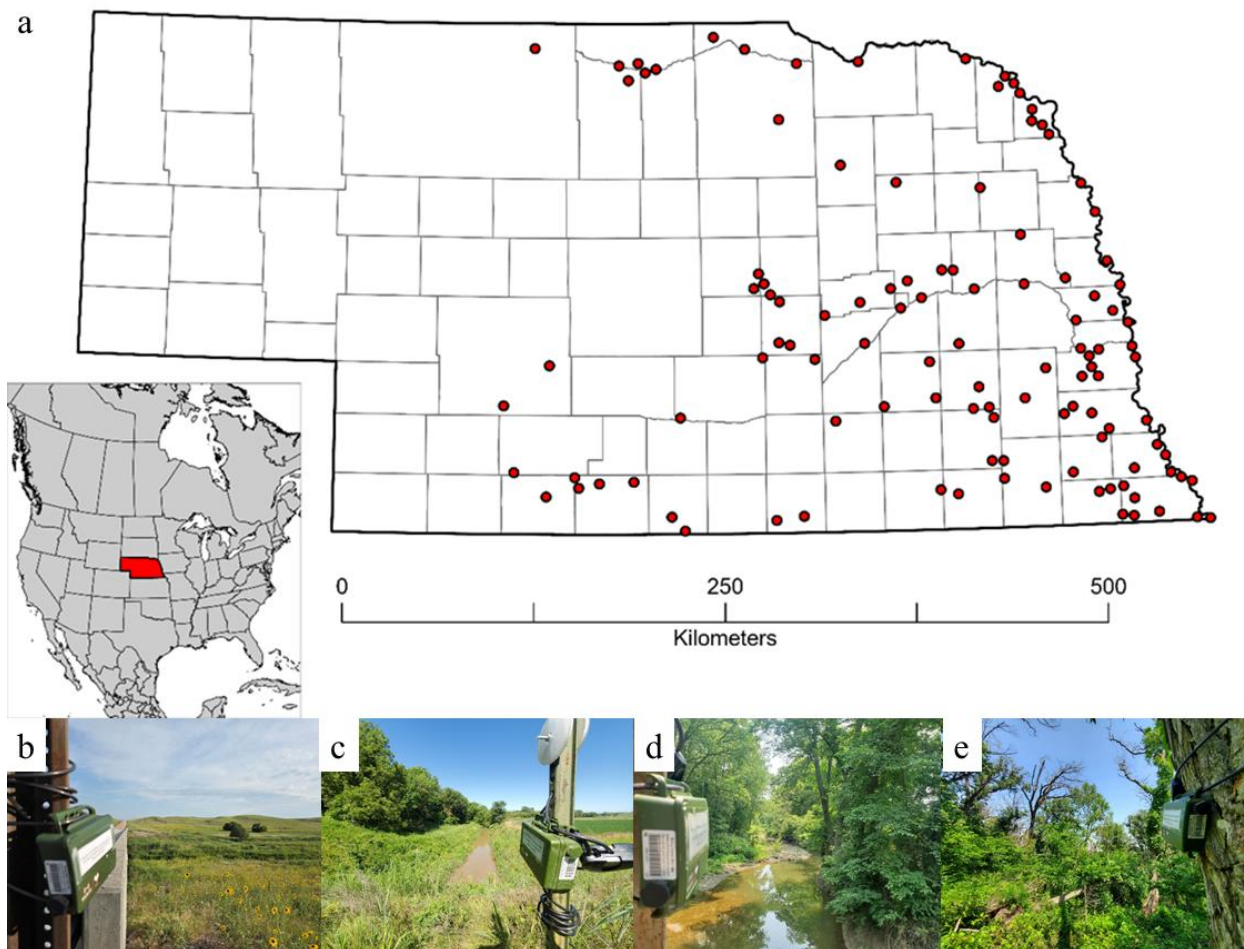


Fig. 2 Case 2 bat acoustic monitoring sites in Nebraska and the state's location in the United States (a), representing the temperate grassland ecosystem. North American Bat Monitoring Program stationary point survey was conducted at these sites in 2024 and site soundscape was characterized. Examples of site physical structure observation photos show field (b), edge (c), corridor (d), and interior (e) based on the soundscape characterization protocol.

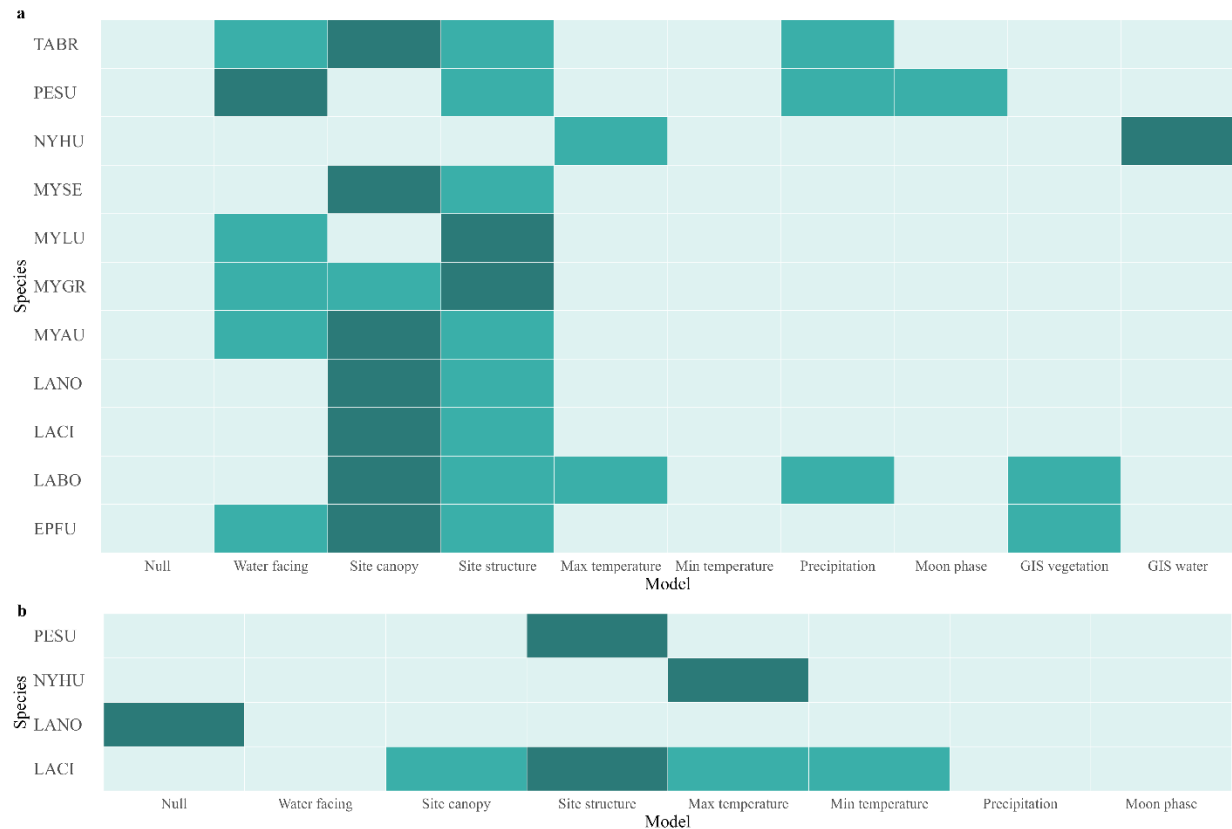


Fig. 3 Single variate hierarchical occupancy models examined and ranked for species specific detection probability estimation in Case 1 (a) and 2 (b). Shades of color indicate model ranking. The top model ranked by Akaike Information Criterion (AIC) is labeled by the dark shade of green. Other models that reduced the null model (no survey variate, constant only) AIC by 2 or more are labeled by intermediate shade of green. All other models that did not perform better than the null model are labeled by light shade of green. Species abbreviations: EPFU (*Eptesicus fuscus*), LABO (*Lasiurus borealis*), LACI (*Lasiurus cinereus*), LANO (*Lasionycteris noctivagans*), MYAU (*Myotis austroriparius*), MYGR (*Myotis grisescens*), MYLU (*Myotis lucifugus*), MYSE (*Myotis septentrionalis*), NYHU (*Nycticeius humeralis*), PESU (*Perimyotis subflavus*), TABR (*Tadarida brasiliensis*).

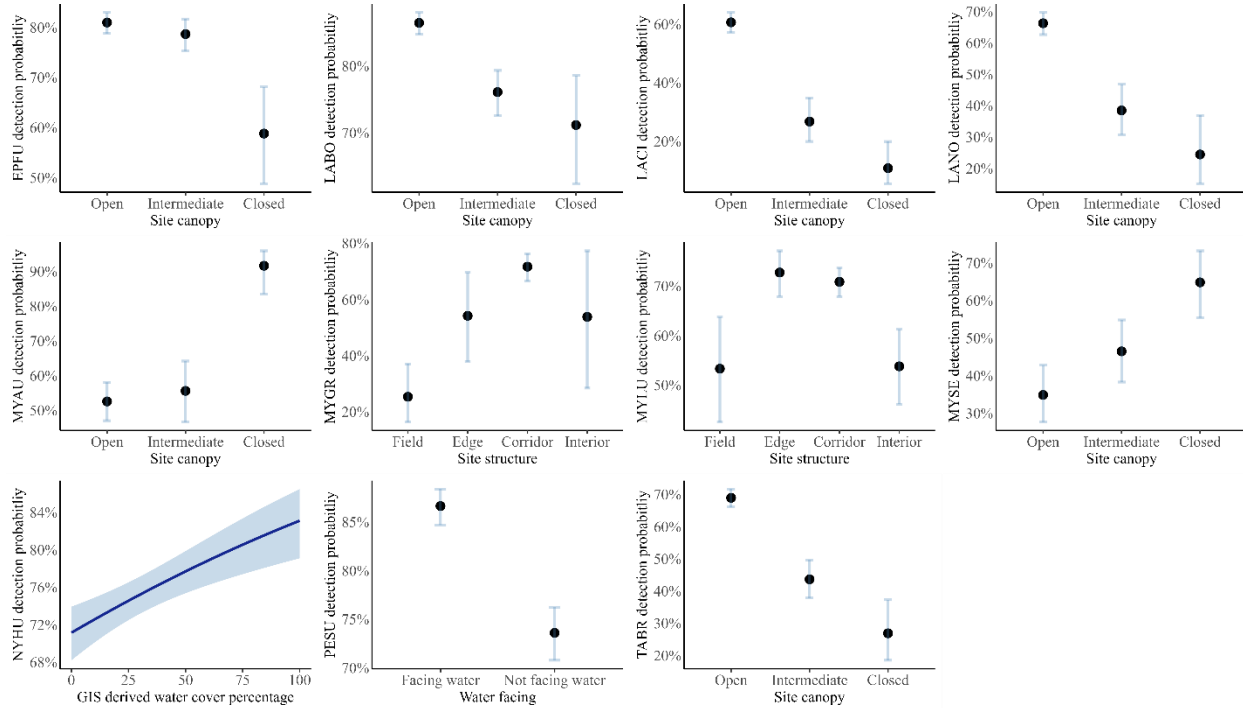


Fig. 4 Relationship between detection probability and corresponding soundscape characterization or other variables in the top detection probability estimation models for each species in Case 1. Estimated detection probability with 95% confidence interval is plotted against soundscape characterization or other variables. Species abbreviations: EPFU (*Eptesicus fuscus*), LABO (*Lasiurus borealis*), LACI (*Lasiurus cinereus*), LANO (*Lasionycteris noctivagans*), MYAU (*Myotis austroriparius*), MYGR (*Myotis grisescens*), MYLU (*Myotis lucifugus*), MYSE (*Myotis septentrionalis*), NYHU (*Nycticeius humeralis*), PESU (*Perimyotis subflavus*), TABR (*Tadarida brasiliensis*).

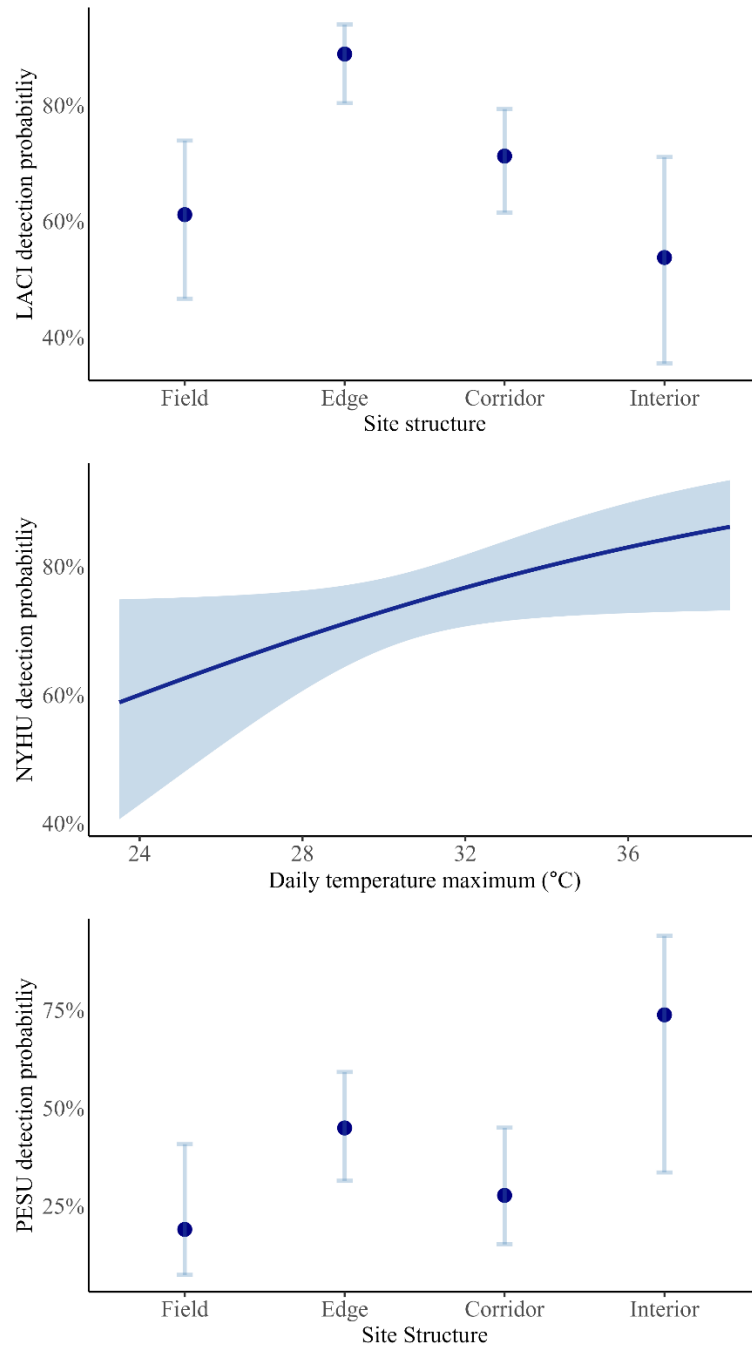


Fig. 5 Relationship between detection probability and corresponding soundscape characterization or other variables in the top detection probability estimation models for each species in Case 2. Estimated detection probability with 95% confidence interval is plotted against soundscape characterization or other variables. Species abbreviations: LACI (*Lasiurus cinereus*), NYHU (*Nycticeius humeralis*), PESU (*Perimyotis subflavus*).