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Quantifying Bat Detection Survey Methods and Activity Patterns

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Quantifying bat detection survey methods and activity patterns

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QUANTIFYING BAT DETECTION AND ACTIVITY PATTERNS

TARA C. HOHOFF

2016

ABSTRACT

Bats have an astonishing diversity and provide vital ecosystem services in an array of different niches. In North America, most species of bats are insectivores and tend to be frequently overlooked for their important ecosystem role providing insect control. As bat populations have declined in recent years, farmers, land managers, conservationists, and bat enthusiasts have wondered what we can do to protect our local bat populations. As a first step, we need to develop methods that more effectively survey for rare species of bats. By performing inefficient surveys, we are doing a disservice to our funding agencies providing misinformation that ultimately puts populations at risk. Our results reveal the low detection probability associated with mist netting of relatively common bats, the big brown (*Eptesicus fuscus*) and little brown bat (*Myotis lucifugus*), compared to the detection probability using full spectrum recorders. These results suggest that acoustic recorders may provide the most robust information and that mist netting alone for presence-absence of species may require additional nights of sampling for accurate results.

We can also manage for bat populations through a better understanding of how they select habitat. In this study we used full spectrum acoustic detectors to sample major land cover types and analyze bat activity patterns at local and landscape scales. Our results indicate that bats in McHenry County most likely use a hierarchical approach to habitat selection and prefer forested riparian areas with large trees that also have numerous small patches of agriculture within a 1 km radius. This information can help us better manage forests for Midwestern bat populations as they hopefully recover from recent population declines.

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INTRODUCTION

Bat research in North America has increased dramatically over the last decade since the onset of white-nose syndrome, a devastating fungal pathogen (Blehert et al. 2009; Frick et al. 2010; Turner et al. 2011), and the increased use of wind turbines (Johnson et al. 2003). The direct fatalities that occur from white-nose syndrome and wind turbines, combined with loss of habitat (Sparks et al. 2005), disturbance to hibernacula (Speakman et al. 1991; Thomas 1995; Johnson et al. 1998), and increased use of insecticides (Wickramasinghe et al. 2004), all may contribute to the recent rapid decline in bat populations. In the wake of these large scale mortalities, wildlife managers have struggled with making informed decisions regarding effective conservation measures for bats due to a lack of baseline data, including incomplete or outdated knowledge about species distributional patterns in areas that have been under-sampled (Miller et al. 2003; Pauli et al. 2015; Rodhouse et al. 2015). To fill this gap, we need effective standard survey techniques to provide comprehensive information on bat distributional patterns. Currently researchers employ two survey techniques—passive surveys with ultrasonic acoustic recording units and active surveys using mist nets (USFWS Indiana Bat Summer Survey Guidelines, 2016). While both survey techniques can produce information about the occurrence of bat species, each has advantages and biases that limit effectiveness.

Using echolocation pulses emitted by bats as an indicator of species presence has several biases that lead to differential detection probabilities among and within species. Acoustic recorders are biased in favor of detecting species that produce loud, mid- to low-range frequency pulses that travel farther in the environment because they attenuate less rapidly

than quieter and high frequency sounds (Lawrence and Simmons 1982, Adams et al. 2012). The density of vegetation at the sampling location may also influence detection due to the reduced detection range from echolocation calls being deflected by habitat features, as well as creating more difficult-to-identify, fragmented call files (Weller and Zabel 1973; Sherwin et al. 2000; O'Keefe et al. 2014). Within forested areas, acoustic detection also may be higher when recorders are located at ponds than along stream sites as bats may forage and circle pond sites increasing opportunities for detection, while at stream sites, they may move in a linear fashion and there may only be one pass at the recorder for detection (Kunz and Brock 1975). There also is a bias associated with the microphone and sensitivity settings used for recording units. Due to the interest in *Myotis* species, many detectors are set to maximize the detection of high frequency calls, which can limit a recorder's ability to detect low frequency species, such as hoary bats (*Lasiurus cinereus*).

In addition to the limitations associated with the collection of acoustic data, there are biases associated with the interpretation of acoustic call data. Specifically, species with distinct vocalizations are more likely to be identified than those that produce echolocation pulses similar to those of other species, regardless of whether classification is performed manually or automatically (Russo and Voigt 2016). Bat call sequences can be difficult to identify to species due to the fact that the sounds emitted are used by all echolocating bats for navigation and prey retrieval (Simmons et al. 1979). Although there may be a communication aspect to bat vocalizations (Thomas et al. 1979; Fenton 2003), the main purpose of echolocation is to collect information for navigation; therefore, there is significant species overlap among echolocation call features, especially for bats that

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utilize similar foraging strategies and environments (Barclay 1999). Comparatively, bird vocalizations are easier to identify due to the species-specific nature of their sounds, which have evolved almost exclusively for communication (Barclay 1999).

Despite these limitations, there is immense potential for using acoustic recorders to estimate bat species distributions because of their ability to collect high volumes of data over long, often uninterrupted, time periods and over a large number of sites and greater diversity of vegetation types with minimal fieldwork. Because acoustic call files provide permanent records, they can be independently verified by other experts or with multiple software programs (Celis-Murillo et al. 2009, Blumstein et al. 2011). Furthermore, with the use of automated acoustic recorders, multiple locations can be sampled simultaneously to better control for nightly variation in environmental conditions. When used simultaneously, acoustic recorders tend to detect more species than mist netting due to the relatively low capture rate associated with mist netting (O'Farrell and Gannon 1999; Robbins et al. 2008).

Mist netting has been a standard method for detecting bat species, particularly prior to the development of ultrasonic recording technology. However, like acoustic recordings, mist nets have inherent biases for detecting the occurrence of species. Mist nets are most effective when deployed within flight corridors such as forested streams or trails, in which the setup can be enclosed within the forest canopy to minimize the probability of bats flying around the net (Kunz and Kurta 1988; MacCarthy et al. 2006). The increased success rate in this type of environment creates a bias that favors the detection of forest-dwelling species. Because nets are less successful in open environments, such as grasslands, wetlands or ponds, it is difficult to capture bat species that prefer these

environments for foraging (O'Farrell and Gannon 1999; Carroll et al. 2002; Morris et al. 2010). Additionally, there is a temporal limitation associated with mist netting due to the fact that most researchers typically begin the survey period at sunset and only continue for up to five hours (current recommendation for Indiana Bat Summer Survey Guidelines by U.S. Fish and Wildlife Service, 2016). This may bias detections against bat species that forage later in the evening compared to an acoustic recorder that is typically deployed for the full night (Skalak et al. 2012). Furthermore, mist nets typically show a decrease in capture rate with successive nights of sampling; such decreases should not occur with acoustic monitoring (Winhold and Kurta 2008). Another challenge associated with mist netting is the capture of endangered or threatened bats, which may put them at risk for injury (Sikes and Animal Care and Use Committee of the American Society of Mammalogists 2016). Despite these limitations, mist nets are frequently used to gain information that cannot be acquired by acoustic recorders, such as the identification of individuals through marking, which allows for estimates of abundance. Researchers also can confidently determine species, which is essential for documenting the occurrence of species with similar call characteristics, as well as acquire information on population structure and growth by identifying sex, age, and reproductive condition (O'Farrell and Gannon 1999).

Variables other than method, such as temperature, may also affect the probability of detecting bats and our ability to describe species occupancy patterns. Higher temperatures likely result in higher detection probabilities of bats (Yates and Muzika 2006), because they are associated with larger insect populations (Frazier et al. 2006), which have been linked to increased bat activity (Wickramasinghe et al. 2004; Threlfall et al. 2012).

Enhanced bat activity in relation to insect abundance should increase species detections across both methods (MacKenzie et al. 2006). Because of the biases associated with detecting bats using acoustic recordings and mist nets, as well as potential differences in detection among species, it is unclear which method should be utilized and how.

Imperfect detection of individuals and species is pervasive in wildlife sampling, as some individuals of a species are present at a survey location during the survey period but are not detected. If not corrected for, imperfect detection can result in biased estimates of species occupancy, leading to erroneous conclusions about species' distributions, habitat associations and temporal trends, especially if species' detection probability varies spatially or temporally. Such biases can translate into flawed management strategies. Occupancy modeling uses patterns of species detection/non-detection over a series of visits to each survey location to estimate species occupancy rates (*i.e.* probability of a species occurring at a location) while accounting for imperfect detection (MacKenzie et al. 2006, Donovan and Hines 2007). Occupancy modeling uses a maximum likelihood approach to estimate detection probabilities in relation to environmental variables (e.g., vegetation type, tree density, temperature), species characteristics (e.g., call frequency) and method (e.g., acoustics, mist-netting; MacKenzie et al. 2006, Nichols et al. 2008) to improve the accuracy of species occupancy patterns. While occupancy modeling can adjust for imperfect detection probability, evidence from simulation studies suggests that occupancy estimates can be biased when detection probabilities are low, especially when few (e.g., two) visits are made to each survey location (MacKenzie et al. 2002), as is generally the case with acoustic and mist-net sampling. However, our knowledge of how detection probability differs between these two methods and in relation to habitat

variables, weather and species is scarce. Previous studies have compared these two survey methods for detecting species; however, these studies used zero-cross recorders (Murray et al. 1999; O'Farrell and Gannon 1999; Robbins et al. 2008), which typically record less calls than full-spectrum recorders (Adams et al. 2012), and did not account for imperfect detection of each method. One similar study that utilized occupancy modeling focused on *Myotis sodalis* only (Kaiser and O'Keefe 2015).

Here, we use multi-method occupancy modeling (Nichols et al. 2008) to compare detection probabilities (Guzy et al. 2014) of bat species with high- and low-frequency vocalizations (*Myotis* sp. and *Eptesicus fuscus*, respectively) between full-spectrum ultrasonic recorders and mist nets. Specifically, we evaluated variation in detection probability between the two techniques in relation to vegetation density (or clutter), nature of foraging areas (pond vs. stream), survey day (first vs. second) and temperature. By evaluating spatial and temporal patterns in detection probability for multiple species and under a range of environmental conditions, our findings will provide guidance regarding the most appropriate method for sampling bat communities and how to implement each method to maximize detection probabilities and the accuracy of species occupancy patterns across spatially and temporally varying environments.

This study was conducted in Illinois, within the North American Midwest region, where bats play a crucial economic role in pest control by consuming large quantities of agricultural insect pests (Maine and Boyles 2015). Unfortunately this area has experienced drastic population declines making bats increasingly difficult to detect (Kaiser and O'Keefe 2015), thereby increasing the demand for efficient survey

techniques. There is evidence that detection may be influenced by region (Duchamp et al. 2006) making this study especially relevant in this area.

MATERIALS & METHODS

STUDY AREA.— All capture and acoustic sampling were conducted within McHenry County Conservation District property in northern Illinois (Figure 1.1). The parks utilized in this study were widespread throughout the county and the size of the parks we sampled ranged from 10 to 3,412 acres (www.mccdistrict.org). Although parks generally consisted of natural land cover, the surrounding landscapes varied greatly, with some parks embedded in agriculturally dominated areas whereas others were located primarily within suburban landscapes. Survey sites within the parks were chosen based on ability to effectively capture bats—along flight corridors, streams, and pond edges.

MIST NETTING.— We used 38mm-mesh mist nets (Avinet, Dryden, NY), 6m or 9m long depending on the width of the flight corridor, stream or pond edge. We typically used a stacked, two-net array unless low hanging vegetation hindered deployment, in which case we used a single net. Typically, two stacked nets were deployed each night for five hours unless weather conditions became unfavorable (temperature below 50°F, sustained wind over 9mph, or heavy rain). We resampled any sites in which there were less than 3 survey hours. In 2013, we surveyed 15 sites for two nights each (129 total survey hours) between 10 June and 8 August. In 2014 we surveyed five sites for five nights (118 total survey hours) between 3 June and 13 August to increase probability of catching rare species. We recorded forearm length, mass, sex, reproductive status, age and species for each capture. All bat handling followed the American Society of Mammalogists' guidelines,

Eastern Illinois University IACUC 13-004, and USFWS white-nose syndrome decontamination protocols.

ACOUSTICS.— At each mist netting location, we placed an acoustic recorder approximately 10-20 meters from the mist net, with the microphone facing into the same flight corridor as the nets in order to survey the same area while also avoiding recording bats in the nets. We deployed SM2BAT+ recorders (Wildlife Acoustics, Maynard, MA) set to record in full spectrum with a sampling rate of 384kHz using SMX-US microphones. Microphones were attached to PVC poles at a height of 3m and oriented parallel to the ground. Recorders were simultaneously operated each night of mist netting and were deployed all night.

We batch processed acoustic files in Sonobat 3.2.1 MW (Szewczak 2014) and then manually verified vocalizations to the most descriptive species group possible. Any call sequences determined as little brown bat (*Myotis lucifugus)* or Indiana bat (*Myotis sodalis*) were combined due to difficulty in identification, and are hereafter referred to as LUSO. However, the presence of Indiana bats in the region is unlikely due to lack of capture records and survey locations outside the current range map for this species (Feldhamer et al. 2015). Occupancy of each species each night was determined by at least one file with discriminating call characteristics.

ENVIRONMENTAL MEASUREMENTS.— At each acoustic recorder and mist netting location we used a modified point-quarter method to estimate tree density and index vegetation clutter (Weller and Zabel 1973; Gehrt and Chelsvig 2003). In grassland, wetland, developed, and agricultural areas that lacked trees, we recorded tree density as

zero. At the start of each mist netting period, we used a Kestrel 3000 (Kestrel Meters, Birmingham, MI) to measure the ambient air temperature for analysis.

DATA ANALYSIS.—

We combined occupancy data for big brown bats (EPFU) and *Myotis* species (LUSO) into a single dataset (J. Hines 2014), and species was added as a binary covariate in our models to test for differences in detection probability between bats that vocalize using low and high frequencies. We combined data from 2013 and 2014 as both methods were conducted simultaneously at all sites (paired design) and because we assumed that differences in detection probability between the methods would be constant across years (Duchamp et al. 2006; MacKenzie et al. 2006). We created detection histories for the first two survey nights for both methods to keep the models balanced and because many survey protocols recommend two nights of mist netting. We z-scored tree density and temperature in order to scale variables (Donovan and Hines 2007). We created a set of candidate models that included the variables or combinations of variables (additive and/or interactive) that we hypothesized would influence detection probability, including: method, species, water body type (pond vs. stream), tree density (or clutter), survey night (first vs. second) and temperature (Table 1.1). The parameters psi and theta were held constant in all models so that we were exclusively assessing variation in detection probability. We evaluated the relationship between detection probability and each variable using multi-method occupancy models in program PRESENCE 11.5 (Hines and MacKenzie 2016). We evaluated models and variables using Akaike Information Criteria (AICc; when n/K<40) values adjusted for small sample sizes, ΔAIC_c, and model weights (Burnham and Anderson 1998). AICc was calculated with an effective sample size of 20

(number of unique sampling units; MacKenzie 2008) We tested the global model for overdispersion ($\hat{c}$) using 1000 bootstrap iterations (Burnham and Anderson 1998), and we included the null model for comparison with our top-ranked models ($\Delta AICc \leq 2$).

RESULTS

The global model had a c-hat value of 1.1651 suggesting that the model structure was adequate; therefore, more parsimonious models are most likely acceptable (Burnham and Anderson 1998). Two models had ΔAIC_c values less than 2, suggesting uncertainty in selecting a specific "best" model. The top-ranked model included method and species (model weight of 0.3996), and the second model included method, species and temperature (model weight of 0.1906), suggesting that method and species had a strong influence on detection probability (Table 1.1). There was no evidence in support of the null model that method did not influence detection. The null model had a ΔAIC_c value of 58.75, with a negligible model weight, indicating that the inclusion of method and species in the model provided a much better fit to our patterns of detection than the null model. Furthermore, method appears in all of the models with a $\Delta AIC_c \leq 17.55$, and species appears in all of the models with a $\Delta AIC_c \leq 4.70$, providing additional evidence supporting the hypothesis that method and species are strongly related to detection probability.

Detection probability was higher using acoustic surveys than mist nets, and EPFU had a higher detection probability than LUSO using both methods (Figure 1.1). There is some, albeit weak, evidence supporting the hypothesis that detection probability of LUSO is affected more by survey method than EPFU, as the method*species model had a ΔAIC_c of 3.47. In the top model, detection probability estimates of EPFU species with acoustic

recorders were more than twice the probability of mist netting. Detection probability estimates for LUSO species were more than six times higher using acoustic recorders than mist netting in the top model.

There was strong support for the influence of temperature on detection probability when method and species were included. Temperature had a positive effect on detection probability, although the effect size was small (Table 1.2). Additionally, there was some support for the effect of night and waterbody. Detection probability was higher for ponds than streams (Figure 1.2) and higher for the first night than the second night for both methods (Figure 1.3).

DISCUSSION

Our data supported the hypothesis that survey method had a substantial influence on detection probability of the species investigated in this study. The higher detection probability with acoustic recorders than mist net surveys was expected. However, the degree of difference was noteworthy and supports previous claims that survey methods are most effective and generate the highest possible detection probabilities when used in conjunction (Murray et al. 1999; Robbins et al. 2008). The results of our study especially raise concerns for conservation and management groups that may use mist netting alone for rare species presence-absence studies (USFWS Indiana Bat Summer Guidelines, 2016) due to the very low detection rate using mist netting of common species in the region. For mist nets, detection probabilities based on two survey nights were 0.44 for EPFU and 0.14 for LUSO. Based on simulation studies, MacKenzie et al. (2002) demonstrated that occupancy rates may be biased when detection probabilities are less than 0.3. When only two surveys are made at a location, detection probabilities greater

than 0.5 are required to yield reasonable occupancy rates (MacKenzie et al. 2002) suggesting that two survey nights may be inadequate for the *Myotis* species.

The lack of strong support for models including site night was unexpected, as a decrease in the number of bats captured on the second night of mist netting combined with consistent bat activity levels on acoustic recorders across the two nights is consistent with previous studies (Robbins et al. 2008; Winhold and Kurta 2008). This outcome is likely due to the fact that we focused on occupancy (species presence/absence), rather than abundance or activity. Both species considered in our study are fairly common, which may have increased the likelihood of detecting the species on both nights (MacKenzie et al. 2006).

Interestingly, we found weak support for higher detection probabilities at ponds than streams for both acoustic recordings and mist-nets. While a higher detection probability by acoustic recorders at ponds than streams is consistent with our expectation, as bats may spend more time foraging over ponds leading to an increased likelihood of detection by recorders, the higher detection rate of the two bat species in nets along the edges of ponds was not expected. Nets are commonly placed in stream corridors as the surrounding vegetation is expected to restrict opportunities for bats to fly around the nets, thereby promoting their detection. At some of our sampling locations we were able to place nets within trail corridors leading to the pond edge, which may have increased our ability to capture bats at pond sites. Our findings suggest that prioritizing placement of mist nets at streams over ponds may not be necessary is there is an appropriate flight corridor present.

While temperature was included in our top-ranked model, the effect size was small, calling into question its biological significance. The relatively low influence of temperature on detection in our study compared to previous reports (Threlfall et al. 2012; Kaiser and O'Keefe 2015) may be due to low variation in temperature in our survey. We conducted surveys only when conditions met USFWS guidelines for mist netting, which may have limited temperature variability leading to low power in our analysis. Furthermore, while we did document large differences in detection probability of the two genera, we did not find support for the hypothesis that tree density or clutter affects the probability of acoustic recordings to detect high and low frequency calls.

Future studies to expand on this question of detection probability would greatly benefit from an increase in sample sites including those in different geographic regions and an expansion to other land cover types, particularly a comparison of the two methods in open habitats, like grasslands, agricultural areas and wetlands, in addition to primarily forested habitats we surveyed in our study (Duchamp et al. 2006). Given the large differences in detection probability between bats in forested areas, where mist-nets are expected to have their greatest capture efficiency, comparison of the two methods in more open habitats may reveal even larger disparities. The difference in detection probability between the two species groups investigated provides additional evidence that detection probability varies with species (Adams et al. 2012), although this effect has not always been observed (Duchamp et al. 2006). In order to produce a sufficiently large dataset to analyze the detection probability of rare species, such as *Myotis septentrionalis* or *Myotis sodalis*, an increase in the number of repeat visits to the same sites would be

necessary since high non-detection rates do not permit precise estimation of detection probability or occupancy rates (MacKenzie et al. 2006).

The results of our study further support the use of multiple methods to obtain the most robust inventory of the local bat population (Kunz and Brock 1975; Murray et al. 1999; Flaquer et al. 2007; Robbins et al. 2008) by quantifying the difference in detection probability between the two methods. We recommend that utilizing mist nets for more rare species (USFWS Indiana Bat Summer Survey Guidelines) should be used with caution unless sufficient survey visits are conducted in order to address the low detection estimates.
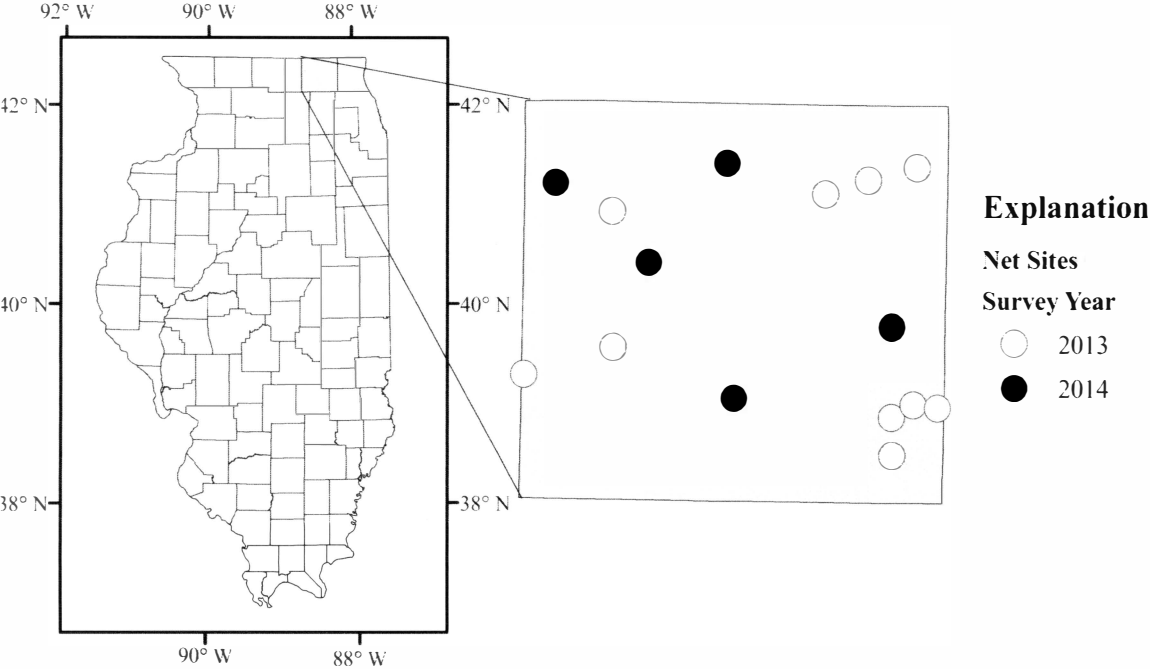
Figure 1.1 Map of mist netting survey sites in McHenry County, Illinois; 2014 sites were also sampled in 2013.

Table 1.1 Candidate models evaluating detection probability using Presence 11.5; psi (Ψ) and theta values were held constant. Bold text denotes models with ΔAICc < 2.00. The global and null models are italicized.

Model	K	AICc	ΔAICc	AIC weight
psi(.)theta(.)p(method+species)	**5**	**157.33**	**0.00**	**0.3996**
psi(.)theta(.)p(method+species+temperature)	**6**	**158.81**	**1.48**	**0.1906**
psi(.)theta(.)p(method+species+night)	6	160.61	3.28	0.0799
psi(.)theta(.)p(method*species)	6	160.80	3.47	0.0726
psi(.)theta(.)p(method+species+waterbody)	6	161.09	3.76	0.0628
psi(.)theta(.)p(method+species+density)	6	161.42	4.09	0.0533
psi(.)theta(.)p(method)	4	162.03	4.70	0.0393
psi(.)theta(.)p(method+species+temperature+night)	7	162.56	5.23	0.0301
psi(.)theta(.)p(method+temperature)	6	163.01	5.68	0.0241
psi(.)theta(.)p(method+night)	5	164.49	7.16	0.0115
psi(.)theta(.)p(method+density)	5	165.26	7.93	0.0078
psi(.)theta(.)p(method+waterbody)	5	165.35	8.02	0.0075
psi(.)theta(.)p(method*night)	4	168.26	10.93	0.0017
psi(.)theta(.)p(method*waterbody)	4	169.32	11.99	0.0010
psi(.)theta(.)p(method+species+temperature+waterbody+night+density)	*9*	*174.88*	*17.55*	*0.0001*
psi(.)theta(.)p(species+temperature)	5	213.64	56.31	0.0000
psi(.)theta(.)p(species)	4	214.03	56.70	0.0000
psi(.)theta(.)p(temperature)	4	215.24	57.91	0.0000
psi(.)theta(.)p(species+night)	5	215.67	58.34	0.0000
psi(.)theta(.)p(.)	*3*	*216.08*	*58.75*	*0.0000*
psi(.)theta(.)p(night)	4	217.35	60.02	0.0000
psi(.)theta(.)p(density)	4	218.64	61.31	0.0000
psi(.)theta(.)p(waterbody)	5	219.25	61.92	0.0000
psi(.)theta(.)p(method*density)	5	220.09	62.76	0.0000
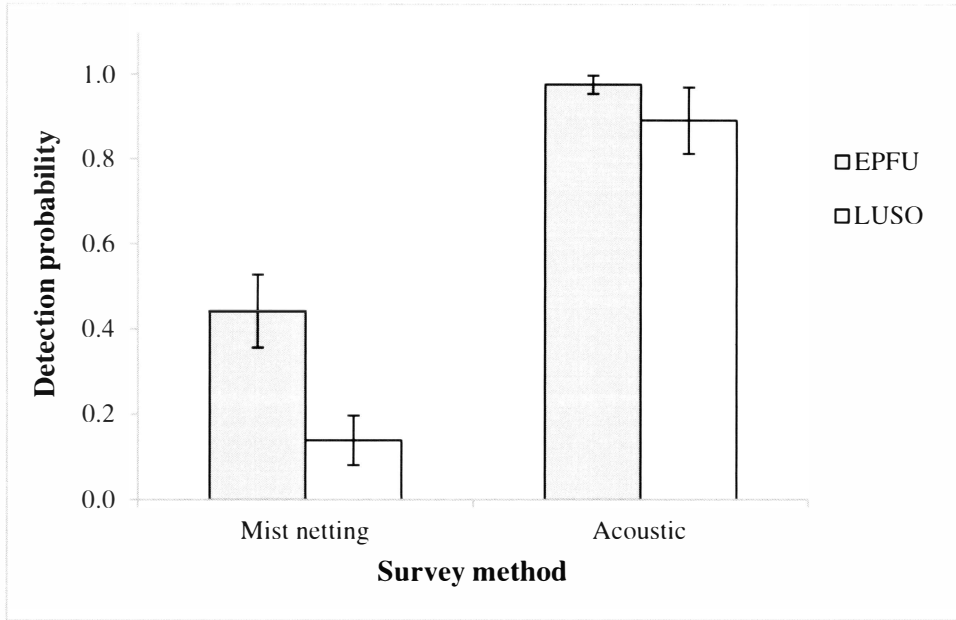
Figure 0.2 Detection probability estimates for top model (model weight estimate =0.3996) in which method and species are detection covariates. EPFU = *Eptesicus fuscus* and LUSO = *Myotis lucifugus* and *M. sodalis* combined.
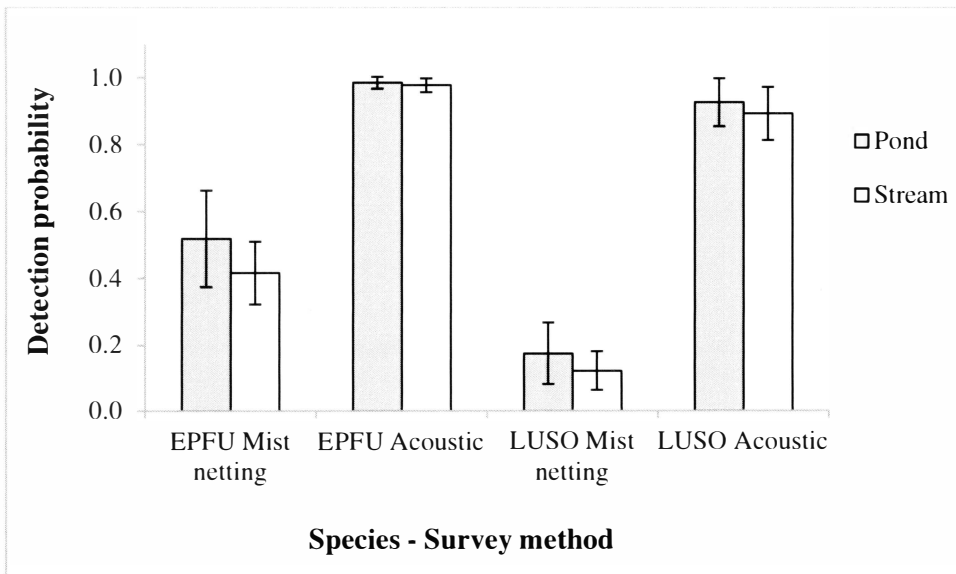
Figure 1.3 Detection probability estimates for model p(method+species+waterbody) in which detection is influenced by survey method type, species and waterbody. EPFU = *Eptesicus fuscus* and LUSO = *Myotis lucifugus* and *M. sodalis* combined.

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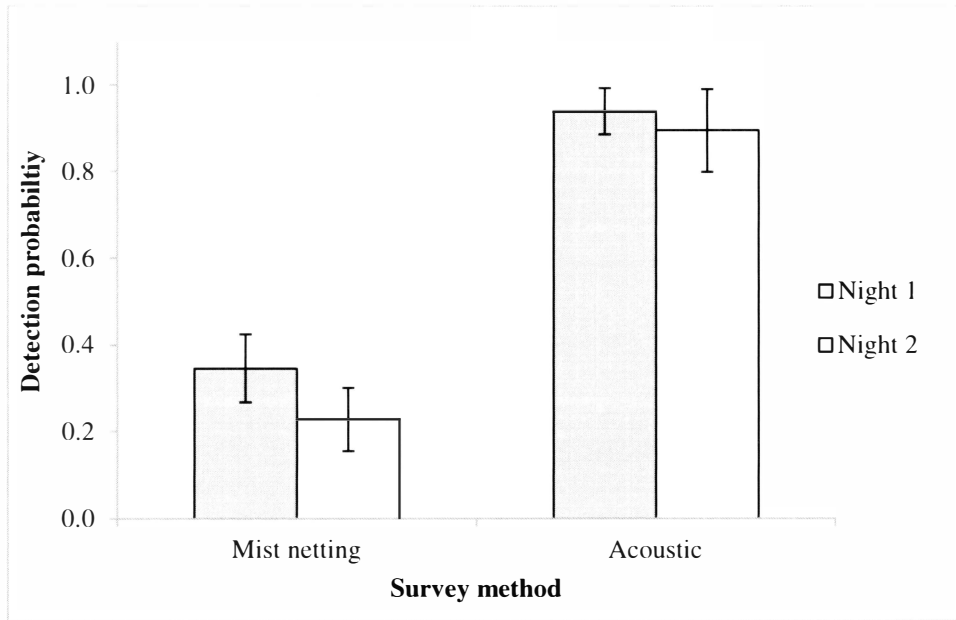
Figure 1.4 Detection probability estimates for model p(method+species+night) in which detection is influenced by survey method type, species and waterbody.

Table 1.2. Model parameters estimates and associated standard error (S.E.) for top models (ΔAICc<5).

Model	Mist netting estimate	S.E.	Acoustic estimate	S.E.	Species estimate	S.E.	Temperature estimate	S.E.	Night estimate	S.E.	Waterbody estimate	S.E.	Density estimate	S.E.
p(method+species)	-1.828	0.487	2.098	0.807	1.594	0.591	-	-	-	-	-	-	-	-
p(method+species+temperature)	-1.845	0.489	2.036	0.815	1.606	0.591	0.001	0.007	-	-	-	-	-	-
p(method+species+night)	-1.059	0.931	2.711	1.041	1.542	0.600	-	-	-0.510	0.536	-	-	-	-
p(method+species+waterbody)	-1.966	0.540	2.112	0.823	1.627	0.594	-	-	-	-	0.412	0.635	-	-
p(method+species+density)	-1.815	0.486	2.046	0.819	1.565	0.601	-	-	-	-	-	-	0.106	0.361
p(method)	-0.871	0.275	2.833	1.029	-	-	-	-	-	-	-	-	-	-

Interaction model	Mist netting EPFU	S.E.	Acoustics EPFU	S.E.	Mist netting LUSO	S.E.	Acoustics LUSO	S.E.
p(method*species)	-0.247	0.337	2.219	0.608	-2.056	0.533	1.996	0.624

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CHAPTER TWO: BAT ACTIVITY IN RELATION TO PARAMETERS AT LOCAL AND LANDSCAPE SCALES

INTRODUCTION

Research on bats as a focal subject in North America has increased dramatically over the last decade since the onset of white-nose syndrome, caused by a devastating fungal pathogen (Blehert et al. 2009; Frick et al. 2010; Turner et al. 2011) and the increased use of wind turbines (Johnson et al. 2003). The direct fatalities that occur from white-nose syndrome and wind turbines, combined with loss of habitat (Sparks et al. 2005), disturbance to hibernacula (Speakman et al. 1991; Thomas 1995; S. A. Johnson et al. 1998), and increased use of insecticides (Wickramasinghe et al. 2004) may all contribute to the recent rapid declines in bat populations. In the wake of these large-scale negative population impacts, it is crucial for bat conservation that we understand relationships between bats and their environmental selection parameters.

There is a wide range of literature available on how bats utilize landscapes, which highlights the complexity of habitat selection. Positive associations with forest patches (Sparks et al. 2005; Medlin et al. 2010) have been reported for bats with forest stand characteristics influencing local habitat usage (Gehrt and Chelsvig 2003; Loeb and O'Keefe 2006). Landscape heterogeneity and patches of non-forested habitat, however, also play a significant role in habitat selection by bats (Yates and Muzika 2006). Bats tend to prefer higher number of patches, which increase edge habitat, and are associated with increased insect abundance where the different landcover types meet (Morris et al. 2010). In addition, presence of water at the local scale has a positive influence on bat activity and abundance (Wickramasinghe et al. 2003; Winhold and Kurta 2008; Dixon

2012). The influence of urban areas on bat activity, however seems unclear. Threlfall et al. (2012) observed that although insect biomass was greater in suburban environments, there was a negative relationship between bat activity and housing density. However, positive relationships between bat activity and urban and agricultural areas have also been reported (Gehrt and Chelsvig 2003). Agriculture has had a positive association as part of some bat species foraging strategies (Duchamp et al. 2004) with Wickramasinghe et al. (2003; 2004) demonstrated that there was higher insect abundance on organic farms, as well as higher bat activity.

In order to test bat habitat associations by local and landscape level factors in northeastern Illinois, we used full spectrum acoustic detectors to record bat activity by sampling in agricultural fields, forest, wetlands, grasslands, and residential areas. At all sites we recorded local factors such as vegetation height and immediate presence of water, as well as measured forest characteristics that had previously been reported as having a significant influence on bat activity (Gehrt and Chelsvig 2003; Loeb and O'Keefe 2006). We created a landcover map with a high degree of accuracy for the survey area to measure landscape level factors. From this research we expected that bat activity would be related to factors at both the local and landscape level. We assumed that bat activity would be locally affected by immediate landcover type, specifically, positively associated with low density forest (Gehrt and Chelsvig 2003) and presence of water (Dixon 2012; Wickramasinghe et al. 2003). At the landscape level, we predicted there would be a positive relationship between bat activity and number of forest patches (Medlin et al. 2010) and a negative relationship with total area of development (Threlfall et al. 2012) and agriculture due to the fact that most of the farming in this region uses

high intensity, conventional methods (Wickramasinghe et al. 2003). We accounted for survey date in analysis since the young of the year would be volant nearing the end of the survey period (Feldhamer et al. 2015) which would increase activity later in the season.

MATERIALS & METHODS

STUDY AREA. — All sampling took place within McHenry County in northeastern Illinois during the summer of 2013 and 2014 (Figure 2.1). The county can be characterized by intensive agriculture, a patchwork of protected nature preserves, and high-density population areas stretching out from Chicago. In 2010, the county population was estimated to be 512 people per square mile (United States Census Bureau 2016). Eight species of bats have been recorded in the McHenry County: the big brown bat (*Eptesicus fuscus*), evening bat (*Nycticeius humeralis*), eastern red bat (*Lasiurus borealis*), hoary bat (*Lasiurus cinereus*), little brown bat (*Myotis lucifugus*), northern long-eared bat (*Myotis septentrionalis*), silver-haired bat (*Lasionycteris noctivagans*), and the tri-colored bat (*Perimyotis subflavus*) (Feldhamer et al. 2015).

ACOUSTICS.— We deployed SM2BAT+ recorders (Wildlife Acoustics, Maynard, MA) set to record in full spectrum with a sampling rate of 384kHz using SMX-US microphones. Microphones were attached to PVC poles at 3m and angled parallel to the ground. Recorders were deployed for two nights in which weather conditions met USFWS guidelines (>50°F, no rain, and no sustained winds over 9mph; USFWS 2013). We utilized Sonobat 3.2.1 MW (Szewczak 2014) to manually verify recorded files to be bat activity by the presence of ≥2 call pulses of similar quality per file. The number of bat activity files was totaled across both nights of recorder deployment and divided by

number of survey hours (30 minutes before sunset to 30 minutes after sunset) for calculation of bat activity per hour.

HABITAT SAMPLING.—At each acoustic recorder location, we collected data on the local habitat characteristics. We used a modified point-quarter method to estimate tree density (Gehrt and Chelsvig 2003) in forested locations to obtain mean distance to plant, which was then calculated into density (1/mean plant distance^2). We recorded the diameter at breast height (DBH) of the tree closest to the center of the vegetation survey plot within each of four quadrants. We used a densiometer to measure canopy cover in each of the quadrants and took the mean of the 4 measurements as an estimate of canopy cover per sample site.

We created a landcover map of McHenry County using 2014 NAIP imagery at 1 meter resolution in ArcMap 10.2 (ESRI 2013). We digitized the landcover into polygons and roads were entered from the TIGER/line shapefile via the US Census Bureau (2013). We created a topology with the data to identify potential errors in digitizing such as gaps between or overlap in polygons. When the topology errors had been resolved, we converted the data to raster format with a cell size of 2m and clipped using the Split Raster tool with a 1km buffer (Perry et al. 2008; Dixon 2012) around each acoustic recorder location. We exported each buffer into a tiff image, which was then entered into Fragstats Version 4.2 (McGarigal et al 2015) for measurement of landscape level metrics—patch richness, number of patches, and mean patch size and class level metrics—total area, number of patches, mean patch size, and largest patch index.

DATA ANALYSIS.—

The number of files verified as bat calls over the two nights divided by the total number of survey hours was rounded to the nearest whole number to retain the count data structure for bat activity per hour. We plotted bat activity per hour as a function of each independent variable using ggplot (Wickham 2009) in R (R Foundation for Statistical Computing, 2014) in order to explore preliminary associations.

In order to reduce the number of variables of interest, the relationship between bat activity and the independent variables at both local and landscape level, were analyzed using the cor.test tool in R with Kendall's tau (because of ability to handle ties more effectively). Any variables that had a significant association ($p=<0.05$) with bat activity were then part of the reduced model set, and variables that did not appear to have an influence on bat activity by hour were removed from further analysis. The remaining variables were analyzed using a Kendall's tau correlation matrix in R to avoid using highly correlated data within models.

We utilized a model-fitting approach to analyze the data by creating a model with each single variable of the reduced dataset with a generalized linear model with negative binomial distribution and log link (Bolker et al. 2009; Morris et al. 2010; Dixon 2012), which was the best fit for over-dispersed count data (Zuur et al. 2009). Models were compared using Akaike Information Criterion (AIC; Burnham and Anderson 1998) and compared to a null model, with only intercept as a variable. We created single term models with all of the variables from the reduced model set. We then expanded on those models with variables that explained more variation than the null model or were within 2 ΔAICc of the null model. We continued to add terms to the models as long as they were

likely to explain more variation than simpler models, while avoiding entering highly correlated variables into the same models (correlation coefficient >0.5). The top models with ΔAICc less than 7 were model averaged (Burnham and Anderson 1998).

RESULTS

We tested the accuracy of the available classified landcover maps (such as the National Land Cover Database 2011) as well as created a map using training data to auto-classify a landcover map from satellite imagery. Neither method resulted in the historically acceptable accuracy of 85% (Anderson 1976) or recently suggested 90% (Shao and Wu 2008) when using sampled points for landcover verification. Due to the recent evidence that errors in landcover classification can have a compounded effect on the calculated landscape metrics (Shao and Wu 2008), we ultimately digitized the study area by hand.

We sampled a total of 109 acoustic survey locations with 21 sites repeated in the second year. We manually verified 30,333 files as bat activity (Table 2.1). At 4 sites the acoustic detector recorded zero bat files and there were 7 sites in which the number of bat files recorded over two nights exceeded a thousand. When accounting for survey effort, mean bat activity per hour was 16.58 with the majority of sites having between one and twenty bat call files per hour (Figure 2.2).

Thirteen variables had significant correlations with bat activity per hour (Table 2.2) and were part of the reduced dataset. Six of the thirteen variables were associated with patches including mean patch size, largest forest patch index, total number of patches, number of agricultural patches, number of forest patches, and number of grassland patches in the 1-kilometer buffer. The only negative correlations in relation to bat activity were mean patch size and year (Table 2.2).

The presence of water at the sampling location and mean DBH at the local site were strong predictors of bat activity with ΔAICc of less than 2 in the single variable models (Figure 2.3; Table 2.3). Water presence had the highest model average estimate (0.66) of significant model average terms. The number of agriculture patches appeared in 6 of the 7 top models with a positive effect on bat activity from model average (Table 2.4). Mean DBH also had a positive relationship with bat activity and appeared in the top three models (Figure 2.3; Table 2.3). We could not enter mean canopy cover, tree density, and local forest site into models with mean DBH due to high correlation values.

DISCUSSION

Local site variables likely influence bat activity as evidenced by presence of water and mean DBH appearing in the top models. The presence of water at the sampling location had a relatively strong, positive influence on bat activity levels, which was predicted from the literature (Wickramasinghe et al. 2003; Owen et al. 2004; Ford et al. 2006; Dixon 2012). Mean DBH as a predictor in bat activity along with the significant correlation ($p=0.00261$) between bat activity and local forest site, suggests that bats in McHenry County likely prefer to forage in mature forest patches. This was expected from Gehrt and Chelsvig's 2003 study in the area and assumptions from studies focusing on species-specific preferences (Dixon 2012). A preference for forested sites with water present reiterates the importance of protecting riparian areas as an important resource for bats, with *Myotis* species in particular typically selecting this type of habitat (Owen et al. 2004; Sparks et al. 2005; Dixon 2012).

In the study by Gehrt and Chelsvig (2003), the density of trees was a significant variable in predicting bat activity but the mean DBH was not. We observed density having little

influence on bat activity, whereas mean DBH was a significant parameter in predicting bat activity. Higher bat activity has been reported in old growth forest compared to second growth forest (Krusic et al. 1996; Zimmerman and Glanz 2000; Erickson and West 2002). Presumably, these older trees had characteristics that bats preferred such as larger DBH. Forest stands with larger DBH than similar forests in the area with smaller DBH are most likely older and will tend to have preferred roosting characteristics such as cracks, crevices, peeling bark, or snags necessary for some Illinois species of bats (Carter and Feldhamer 2005) .

At the landscape scale, both number of agricultural patches and number of grassland patches appeared in top models. We predicted patch density would influence bat activity due to the association of edges with increased insect abundance (Morris et al. 2010). However we assumed that forested patches would be a predictor of bat activity (Sparks et al. 2005; Medlin et al. 2010) but this was not evidenced in the top models. The importance of non-forested landcover in the landscape for some species of bats has been reported previously (Yates and Muzika 2006; Dixon 2012) and agricultural fields in conjunction with forest patches may provide a high-contrast edge suitable for foraging (Duchamp et al. 2004). The positive relationship with number of agricultural patches may also be influenced by an avoidance of high intensity conventional agriculture (Wickramasinghe et al. 2003) in which there are large continuous patches of agriculture that may be associated with lower insect abundance (Wickramasinghe et al. 2004). There was no relationship detected with urban areas (Table 2.2), which was unexpected (Gehrt and Chelsvig 2003; Threlfall et al. 2012), but may have been a function of lower number of sampling sites compared to forest, agriculture, and grassland sites (Table 2.1).

In this study, we were limited to only accounting for bat activity and not species-specific occupancy due to the large volume of calls recorded (>30,000). Having species level data most likely would have resulted in better models due to species typically selecting roosting and foraging locations based on species-specific requirements (Gehrt and Chelsvig 2004; Perry et al. 2008; Dixon 2012). However the importance of providing land managers with guidance on how to manage habitat for all bats, not just those listed as threatened is a useful endeavor as more species of bats are rapidly being considered for protection (Frick et al. 2010). It is also important for us to keep our common bats common and maintain species diversity as bats provide vital insect control (Boyles et al. 2011; Maine and Boyles 2015) and different species of bats prey on different insect groups (Anthony and Kunz 1977; Aldridge and Rautenbach 1987; Whitaker 1995). This study reiterates the importance of wooded riparian areas with larger diameter trees adjacent to small agriculture patches areas as high priority sites for bat conservation management.
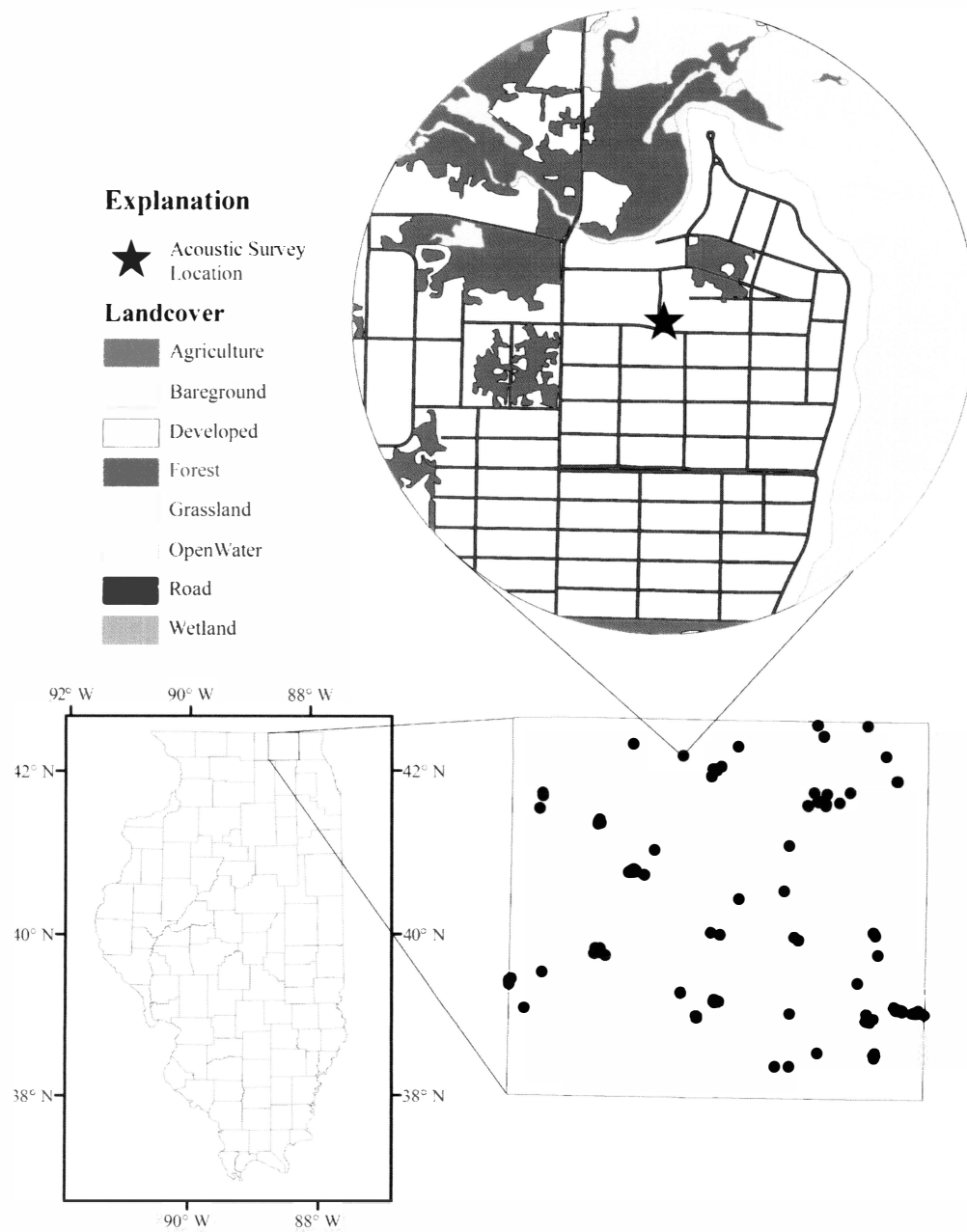
Figure 2.1. Map of 2013 & 2014 survey area in relation to the state of Illinois, as well as a magnified view of one of the survey buffer points to highlight the detail in the associated landcover map.

Table 2.1. Total acoustic sampling sites per landcover type during summer 2013 and 2014 throughout McHenry County, Illinois.

	Agriculture	Developed	Forest				Grassland				Wetland	*Total*
			Pond	Stream	Non-Riparian	Total	Pond	Stream	Non-Riparian	Total		
Total	12	13	5	15	17	37	7	9	27	43	4	109
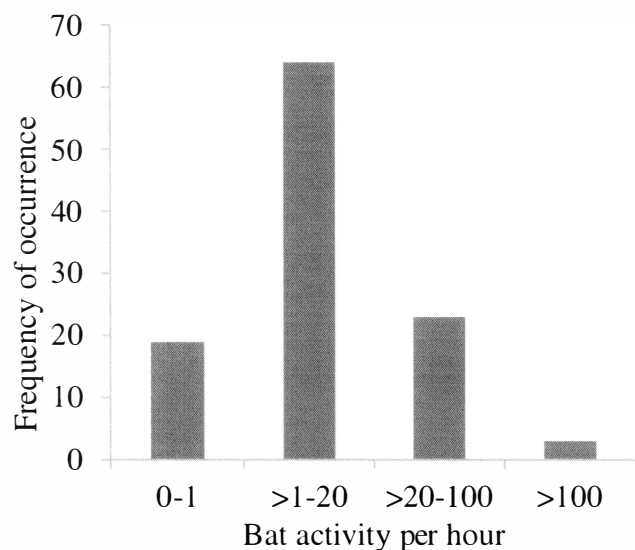
Figure 2.2. Distribution of collected bat activity files recorded at the 109 sites sampled using full spectrum acoustic recorders.

Table 2.2. Independent variables with significant correlation with bat activity using Kendall's tau correlation test in R (DBH=diameter at breast height; LPI=largest patch index).

Variable	Correlation coefficient	p-value
Mean DBH	0.292	0.00001
Tree density	0.260	0.00040
Local water presence	0.281	0.00050
Mean canopy cover	0.236	0.00136
Local site forest	0.243	0.00261
Total area of forest	0.183	0.00539
Number of agriculture patches	0.177	0.00984
Number of forest patches	0.168	0.01223
Number of grassland patches	0.156	0.02005
Total number of patches	0.139	0.03716
Mean patch size	-0.138	0.03864
Forest LPI	0.135	0.04224
Year	-0.161	0.04592
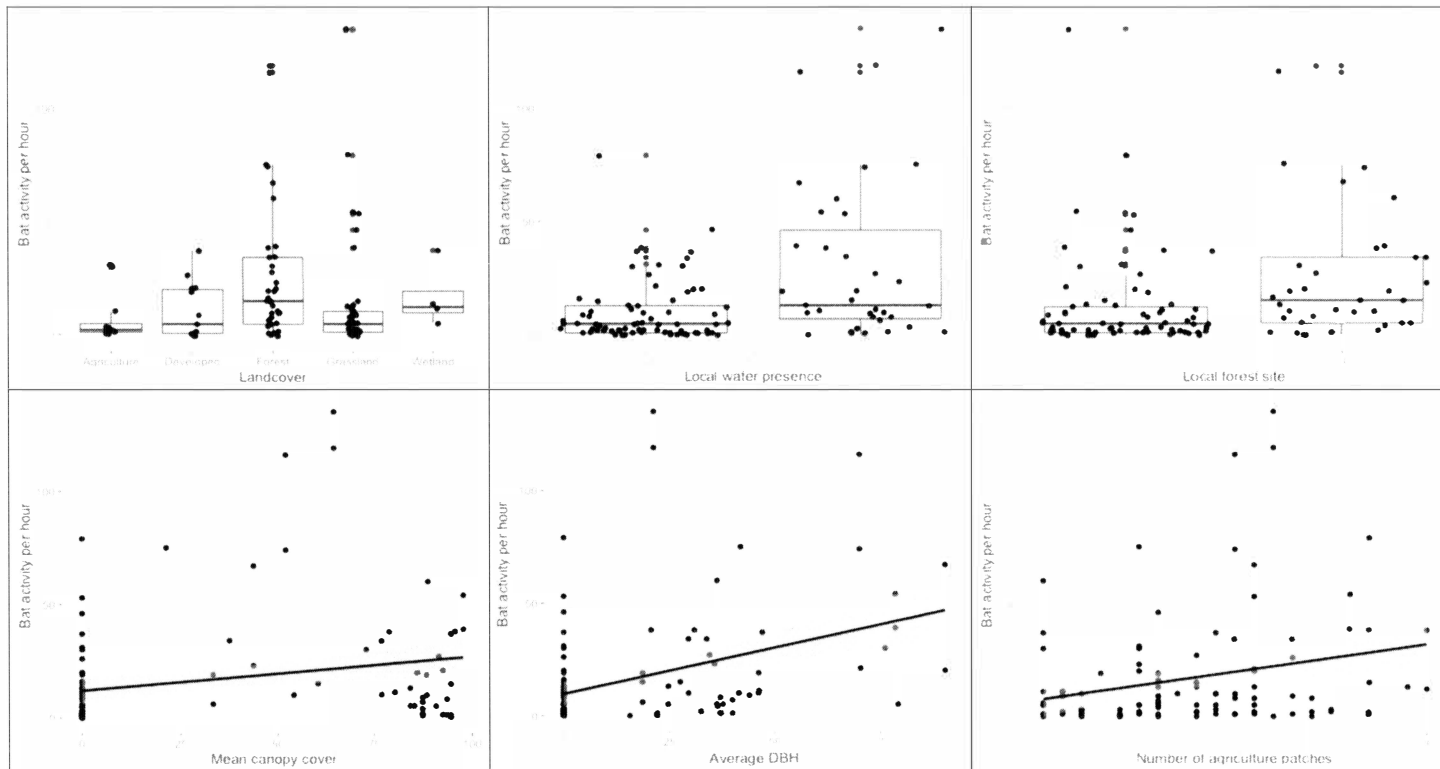
Figure 2.3. Relationship of local and landscape level variables with bat activity per hour at 109 acoustic sampling locations. Plots created using ggplot2 (Wickham, 2009).

Table 2.3. Models created through the model-fitting approach and associated information utilized in model selection process. Models in bold were used for model average and null model italicized.

| Model	degrees of freedom	log-likelihood	AICc	ΔAICc	weight
Water + Number of agriculture patches + AvgDBH	**5**	**-388.77**	**788.12**	**0.00**	**0.5537**
Water + Number of agriculture patches + AvgDBH + Number of grassland patches	**6**	**-388.31**	**789.44**	**1.32**	**0.2860**
Water + AvgDBH + Number of grassland patches	**5**	**-391.06**	**792.69**	**4.57**	**0.0563**
Water + Number of agriculture patches + Canopy cover	5	-392.37	795.33	7.21	0.0151
Water + Number of agriculture patches + Local forest site	5	-392.60	795.78	7.66	0.0120
Water + Number of agriculture patches + Year	5	-392.64	795.87	7.74	0.0115
Water + Number of agriculture patches	4	-394.13	796.65	8.53	0.0078
Water + AvgDBH	4	-394.16	796.71	8.58	0.0076
Water + AvgDBH + Number of forest patches	5	-393.36	797.29	9.17	0.0056
Water + Number of agriculture patches + Number of grassland patches	5	-393.69	797.96	9.83	0.0041
Water + Number of agriculture patches + Total forested area	5	-393.71	797.99	9.87	0.0040
Water + AvgDBH + Year	5	-393.76	798.11	9.98	0.0038
Water + AvgDBH + Number of patches	5	-393.87	798.33	10.20	0.0034
Water + Number of agriculture patches + Number of forested patches	5	-393.89	798.36	10.24	0.0033
Water + Number of agriculture patches + Forest LPI	5	-394.02	798.62	10.50	0.0029
Water + Number of agriculture patches + Tree density	5	-394.04	798.66	10.53	0.0029
Water + AvgDBH + Total forested area	5	-394.07	798.72	10.60	0.0028
Water + Number of agriculture patches + Number of patches	5	-394.09	798.76	10.64	0.0027
Water + AvgDBH + Mean patch size	5	-394.11	798.80	10.68	0.0027
Water + Number of agriculture patches + Mean patch size	5	-394.13	798.84	10.72	0.0026
Water + AvgDBH + Forest LPI	5	-394.15	798.88	10.75	0.0026
Water + Number of grassland patches	4	-395.55	799.49	11.37	0.0019
Water + Canopy cover	4	-396.57	801.52	13.39	0.0007
Water + Year	4	-396.59	801.56	13.44	0.0007
Water	3	-397.74	801.71	13.58	0.0006
Water + Local forest site	4	-396.70	801.78	13.66	0.0006

Water + Number of forest patches	4	-396.76	801.89	13.77	0.0006
Water + Total forest patches	4	-397.05	802.49	14.36	0.0004
Water + Number of patches	4	-397.41	803.20	15.08	0.0003
Mean DBH	3	-398.53	803.28	15.16	0.0003
Water + Tree density	4	-397.61	803.60	15.47	0.0002
Water + Mean patch size	4	-397.61	803.60	15.48	0.0002
Water + Forest LPI	4	-397.61	803.60	15.48	0.0002
Mean canopy cover	3	-402.77	811.77	23.65	0.0000
Number of agriculture patches	3	-402.78	811.78	23.66	0.0000
Number of grassland patches	3	-402.81	811.85	23.73	0.0000
Local forest site	3	-403.73	813.68	25.56	0.0000
Total forest area	3	-404.47	815.18	27.05	0.0000
Number of forested patches	3	-405.03	816.30	28.17	0.0000
Intercept model (null model)	*2*	*-407.66*	*819.44*	*31.32*	*0.0000*
Tree density	3	-406.91	820.04	31.92	0.0000
Forest LPI	3	-407.00	820.22	32.10	0.0000
Number of patches	3	-407.06	820.35	32.23	0.0000
Year	3	-407.17	820.56	32.44	0.0000
Mean patch size	3	-407.20	820.62	32.50	0.0000

Table 2.4. Parameter estimates of conditional model average from top three models created through model-fitting approach.

Variable	Estimate	Adjusted standard error	z-value	p-value
Intercept	1.48	0.24	6.17	<0.001
Water	0.66	0.26	2.54	0.011
Number of agriculture patches	0.07	0.02	2.89	0.004
Mean DBH	0.02	0.00	3.26	0.001
Number of grassland patches	0.01	0.01	1.00	0.317

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