USING ACOUSTIC SPATIAL CAPTURE-RECAPTURE TO ESTIMATE OWL POPULATION DENSITY AND THE EFFECTS OF ANTHROPOGENIC FACTORS IN THE CHATTAHOOCHEE RIVER NATIONAL RECREATION AREA

by

LILY HELEN MARTIN

(Under the Direction of Jeffrey Hepinstall-Cymerman)

ABSTRACT

Passive acoustics may offer advantages over traditional survey methods for estimating population trends of cryptic species that are difficult to monitor. To assess the utility of acoustic spatial capture-recapture methods (SCR) for estimating population density of owl species, we conducted passive acoustic surveys for Barred Owls, Great Horned Owls, and Eastern Screech-Owls in a protected park within a rapidly urbanizing area of Georgia. Acoustic SCR provided reliable estimates of Great Horned Owl density consistent with previous studies in other parts of the species' range. Great Horned Owl density was modelled as a function of multiscale landscape and anthropogenic variables, including noise and light pollution. Forest cover, edge density, and anthropogenic noise at the local scale were the most important predictors of owl density in the study area. Our findings indicate the efficacy of acoustic SCR for owl population monitoring and provide important management implications for those within highly urbanized areas.

INDEX WORDS: Density, Passive acoustics, Spatially explicit capture-recapture, Urbanization, Anthropogenic noise, Strigiformes, Georgia

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Introduction and Literature Review

Avian population monitoring

Effective conservation strategies require understanding of wildlife population dynamics obtained through reliable monitoring techniques. Monitoring of avian populations traditionally relies on the use of two common methods: point count surveys and mist-netting. Point counts generally consist of an experienced observer recording distance to birds detected by sight or sound from a defined point during a set time period (Rosenstock et al. 2002). These surveys can be conducted in a wide range of habitat types without any specialized equipment. However, human observers can be a source of observational error if their presence affects the normal activity of birds or if their ability to identify species is unreliable (Shonfield and Bayne 2017a). Mist-netting is a capture-recapture method involving the physical trapping and marking of individuals for identification in future encounters. Species counts from mist-netting are relatively unaffected by observer bias. However, in addition to being labor-intensive, this technique is known to under-sample populations due to the limited area that can be effectively surveyed (Dunn and Ralph 2004). Both point counts and mist-netting are extensively used to estimate abundance of avian populations, but alternative methods may offer greater efficacy in monitoring certain cryptic species (Bibby et al. 2000, Dunn and Ralph 2004).

A relatively new avian monitoring technique involves the use of autonomous recording units (ARUs). These devices can be programmed to record sound at times of interest and remain unattended in the field for extended periods. Advantages to this method include reduction in field personnel hours, minimal disruption to wildlife and vegetation, and the creation of a permanent record of audio that can be reviewed numerous times by multiple trained personnel to increase the accuracy of detections. Tradeoffs include time spent in the lab processing recordings, costs of purchasing and maintaining units, the inability to visually identify individuals in the field, and the inability to detect non-vocalizing individuals (Shonfield and Bayne 2017a).

While ARUs have been increasingly used in avian research over the past decade, their efficacy compared to human observers has been highly debated. Shonfield and Bayne (2017a) identified 21 studies that compared point counts to surveys using ARUs and found that although human observers identified more species in some studies, whether it was due to their ability to "hear" farther than the units or detect birds visually, ARUs were generally comparable to humans. The authors went on to suggest this technology should now be used in more innovative ways to study birds. Beyond serving as a replacement for a human observer, ARUs have proven useful in remote locations that are difficult to access at times of interest for surveying, for studying species that are rare or vocalize infrequently (Campos-Cerqueira and Aide 2016, Holmes et al. 2014, Rognan et al. 2009, Zwart et al. 2014), and for nocturnal surveys (Digby et al. 2013, Goyette et al. 2011, Shonfield and Bayne 2017b, Sidie-Slettedahl et al. 2015).

Acoustic spatial capture-recapture

In recent years, passive acoustic data has been used to estimate population density of vocalizing species when collected using a spatially explicit capture-recapture (SCR; Borchers and Efford 2008, Borchers et al. 2015, Efford 2004, Efford et al. 2009a, 2009b, Royle et al. 2013) approach. Acoustic SCR involves using an array of microphones resembling a trapping grid in which the detection of an individual call represents a "capture", and nearly simultaneous detections across multiple microphones are “recaptures” in space. A distance-based detection model is fitted to each received signal, and call density (calls produced per unit area per unit time) is estimated using signal strength as a proxy for distance (Dawson and Efford 2009). In addition, differences in the time-of-arrival of signals at multiple microphones can be incorporated into the model to provide more information about the locations of sound sources and increase precision of the call density estimate (Stevenson et al. 2015). Population density can be estimated from call density if individuals can be distinguished by their calls or a rate of call production is known (Dawson and Efford 2009). Naturally, this estimate of density is only for individuals that vocalize within a population, which excludes juveniles as well as females of some species (e.g., *A. lightfooti*; Measey et al. 2017).

Recent developments to acoustic SCR models have increased precision of density estimates and expanded applicability to more complex habitats without requiring any additional fieldwork. Stevenson et al. (2020) introduced a model to directly estimate the detection function, call rate, and population density from the detection data, eliminating the need to expend time and labor estimating call rate independently in the field. Their method requires that individuals can be identified by their calls, which is becoming increasingly possible for many species with the development of song discrimination techniques (e.g., Ehnes & Foote 2015, Petrusková et al. 2016). Models that account for uncertain individual identities are also in the works (Augustine et al., 2018, 2019). In addition, an inhomogeneous Poisson process for the latent locations of individuals is implemented in the model to allow for estimation of animal density surfaces (Stevenson et al. 2020).

Dawson and Efford (2009) first applied acoustic SCR to ovenbirds *Seiurus aurocapilla*, and its practicality has since been demonstrated for other taxa, including cetaceans (Harris et al.

2013, Marques et al. 2013), primates (Kidney et al. 2016), and frogs (Stevenson et al. 2015, Measey et al. 2017). Despite evidence that density estimates from acoustic SCR are more precise than those obtained from mist-netting (Dawson and Efford 2009), these methods have not been applied to another avian species (Perez-Granados and Traba 2021). For elusive species that are traditionally difficult to monitor, noninvasive acoustic methods appear to offer a solution. Many are lacking reliable density estimates that provide detailed information on population status. Expanding the application of acoustic SCR to more species in a greater variety of habitats could thereby aid conservation planning in identifying those at risk before they are of critical concern. Widening applications may also help refine acoustic methods and propel further model development with extensions to accommodate more complex situations.

Monitoring owl populations

In the U.S., Owls (*Strigidae*) are one group of birds in particular for which population estimates are generally lacking (McClure et al. 2018). Most information available on population trends comes from the North American Breeding Bird Survey (BBS) and Christmas Bird Count (CBC). The BBS is an annual survey during the height of the avian breeding season (June for most species) in which volunteers conduct standardized point counts along roadsides throughout the U.S. and Canada (Sauer et al. 2017). Similarly, the CBC is conducted annually, but during just one day in early winter using less structured census techniques (Bock and Root 1981). The BBS and CBC provide large-scale abundance indices for many species; however, the protocol is unsuitable for detecting most species of owls due to their elusive, nocturnal behavior. Both surveys also occur outside of the typical owl breeding season in early Spring when adults are most vocally active.

A common approach to studying owl populations is the use of call-broadcast surveys (Fuller and Mosher 1981). Broadcasting a recorded owl call during a survey increases the probability of an individual vocalizing and being detected (Kissling et al. 2010). Though this technique is useful in assessing occurrence of a species, it can be problematic for abundance or density estimation, because broadcasted calls may attract owls to areas outside of their established territories. Call broadcasts may also introduce bias into surveys of multiple owl species, because the detection of some species may be affected by the calls of conspecifics (Shonfield et al. 2018). A number of recent studies have used ARUs to conduct passive acoustic surveys of owls as an alternative to broadcast surveys (e.g., Shonfield and Bayne 2017b, Duchac et al. 2020). Passive surveys are unlikely to affect the natural behavior of owls and therefore provide a more realistic assessment of occupancy patterns and density.

Research needs

Owls and other raptors are key predators in many habitats throughout the U.S., serving as important indicators of environmental health. There is growing concern for their populations globally as they are increasingly threatened by habitat destruction and alteration among other factors. Owls are expected to be at an even greater risk due to their non-migratory behavior and dependence on forests. With nearly half of all species estimated to be in decline, the IUCN Red List considers population monitoring to be the highest research priority for owls (McClure et al. 2018). Current information on owl population trends is unreliable, and traditional avian monitoring techniques are not suited for their cryptic nature. Precise estimates of population density are needed to identify species at risk and guide conservation actions. Additional needs include investigating the influence of anthropogenic factors, artificial light and noise in particular, on the distribution and abundance of owls in highly urbanized areas (Ortega 2012, Frohlich and Ciach 2019).

Owls possess several traits that appear to make them an ideal group of species for population density estimation within an acoustic SCR framework. Both sexes produce vocalizations, and they do so frequently during the breeding season to maintain territories and pair bonds. Owls typically call on or near the nest site, so their movements over the course of an acoustic survey can be assumed to be minimal (Bent 1961). Most vocalizations are low frequency sounds that travel long distances; therefore, they are likely to be detected by multiple microphones in an array encompassing a large area of habitat. The vocalizations of some species also possess individually distinct characteristics which allows for the possibility of identifying individuals by their calls (e.g., Zhou et al. 2020). Application of acoustic SCR is necessary to determine if it is a viable technique for estimating owl populations. Successful application will also allow us to assess relationships between owl abundance and factors of urbanization.

Study Overview

This study was developed alongside a long-term avian monitoring project conducted by the National Park Service's Southeast Coast Network (SECN) Inventory & Monitoring Program (I&M). The goal of my research was to employ autonomous recording units to provide information on the population status of owl species found in the Chattahoochee River National Recreation Area (CRNRA), a SECN park located in north Georgia. Owl species present here include Barred Owls (*Strix varia*), Great Horned Owls (*Bubo virginianus*), and Eastern Screech-Owls (*Megascops asio*). Information on these species within the park is limited to occupancy patterns observed over the past decade through the current National Park Service I&M protocol. Few studies have been conducted on owls in Georgia, and there is a general lack of population estimates for all three species throughout the Southeast despite habitat degradation and knowledge of the potential for interspecific conflict where owls coexist (e.g., Hakkarainen and Korpimaki 1996).

Out of 17 parks within the SECN, the CRNRA is considered to have one of the most prominent urban-wildland interfaces with its proximity to the large metropolitan center of Atlanta. (Byrne et al. 2014). The five counties where the CRNRA occurs have experienced some of the fastest population growth in the state over the past decade, and Fulton County, Georgia's most populous county with just over 1 million people (U.S. Census Bureau 2019), borders the majority of the park. Urban areas in this region and across much of the Southeastern Piedmont are projected to expand by 165% over the next 50 years (Terando et al. 2014). More research is needed to predict how owl populations will respond to increasing fragmentation of the natural landscape as well as other factors associated with urbanization (i.e., anthropogenic noise). Monitoring population density over time in response to environmental changes will be key in informing management strategies.

Study Objectives

The objectives of this study were (a) to explore the utility of acoustic SCR for estimating population density of owls by applying methods to species found in the CRNRA (chapter 2); and (b) to investigate the relationship between owl population density and anthropogenic factors in the study area to assess the potential effects on owls within rapidly urbanizing landscapes (chapter 3).

Study Area

This study took place in the Chattahoochee River National Recreation Area (CRNRA), a 4,000-ha park extending 48 miles along the Chattahoochee River between the city of Atlanta, Georgia to the south and Lake Lanier to the north. Land cover here includes uplands with mixed pine and hardwood communities composed of predominantly tulip-poplar (*Liriodendron tulipifera*), American beech (*Fagus grandiflora*), oak (*Quercus spp.*), loblolly pine (*Pinus taeda*), and shortleaf pine (*Pinus 8chinate*) as well as lowland floodplains and riparian areas dominated by canopy species, such as river birch (*Betula nigra*) and green ash (*Fraxinus pennsylvanica*) (Byrne et al. 2014). Much of the area surrounding the park has high intensity urban land cover (i.e., central business districts, multi-family dwellings, commercial, industrial, and institutional facilities) especially where the river nears Atlanta (Figure 1.1). The park hosts a rich avifauna with a total of 192 bird species, including Great Horned Owl, Barred Owl, and Eastern Screech-Owl according to the NPSpecies (2015) list. The CRNRA provides an opportune location to monitor several owl species coexisting in a preserved area affected by anthropogenic stressors from the surrounding landscape under rapid development.

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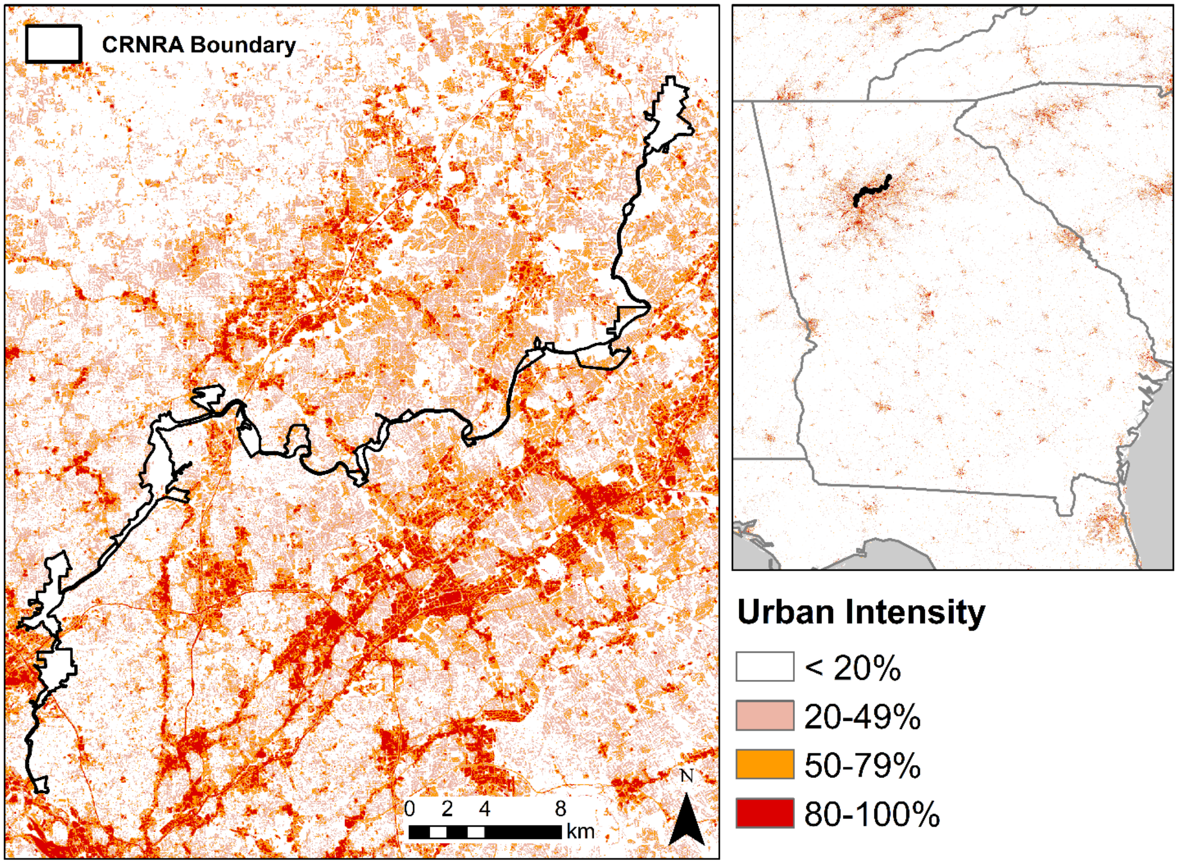

Figure 1.1 Urbanization intensity measured by impervious land cover (%) surrounding the Chattahoochee River National Recreation Area located in north-central Georgia. Data were obtained from the 2019 National Land Cover Dataset (Dewitz 2021).

CHAPTER 2

ESTIMATING POPULATION DENSITY OF OWL SPECIES IN THE CHATTAHOOCHEE RIVER NATIONAL RECREATION AREA

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[1] Martin, Lily H., J. Hepinstall-Cymerman, R. B. Chandler, and M. C. Parrish. To be submitted to *The Condor*.

Abstract

Acoustic spatial capture-recapture (SCR) methods appear useful for estimating populations of cryptic species that are traditionally difficult to monitor. Owls are one such group of species for which population estimates are generally lacking. To assess the utility of acoustic SCR as a reliable technique for estimating owl population density, we conducted passive acoustic surveys for owls over two breeding seasons in a protected park in Georgia. We used a combination of acoustic discrimination techniques to identify individual owls, including spectrogram cross-correlation, hierarchical clustering, and visual scanning. Overall, acoustic SCR produced reliable estimates of Great Horned Owl population density consistent with previous studies in other parts of its range. We provide recommendations to improve acoustic sampling and individual discrimination of owls, and we suggest that acoustic SCR offers important advantages over conventional methods for monitoring cryptic species.

Introduction

Owls and other raptors are key predators in ecosystems around the globe, serving as important indicators of environmental health, cultural symbols, and biological controls of rodent pest populations (Donázar et al. 2016). Their position at the top of the food chain and generally slow life history, however, make them particularly susceptible to anthropogenic threats and local extinctions (Bennett and Owens 1997, McClure et al. 2018). There is growing concern for raptor populations as they are increasingly threatened by habitat destruction and alteration among other factors. Owls are expected to be at an even greater risk due to their non-migratory behavior and dependence on forests. With nearly half of all owl species estimated to be in decline, the IUCN Red List considers population monitoring to be the highest research priority (McClure et al. 2018).

There is a general lack of information available on population trends for most owl species, primarily due to their elusive behavior which makes them difficult to monitor using traditional protocols. The annual North American Breeding Bird Survey (BBS), among other large-scale surveys, provides the majority of estimates, but it is conducted during summer daytime hours when owls are least vocally active (Sauer et al. 2017). The survey design is thus inappropriate for detecting owls, as estimates derived from daytime surveys cannot be considered reliable. Call-broadcast surveys in which a recorded owl call is broadcasted to induce a response are another common method for monitoring owl populations, however these also have several limitations (Fuller and Mosher 1981). Broadcasted calls may attract owls to areas outside of their established territories which is problematic for estimating density. Call broadcasts may also introduce bias into surveys of multiple owl species, because the detection of some species may be affected by the calls of others (Shonfield et al. 2018). For example, the detection rate of

Eastern Screech-Owls may be lower in the presence of larger owl species, such as Barred Owls (Nagy and Rockwell 2013).

A number of recent studies have used autonomous recording units (ARUs) to conduct passive acoustic surveys of owls as an alternative to traditional methods (e.g., Shonfield and Bayne 2017, Duchac et al. 2020). ARUs are particularly useful for studying cryptic species, because they can be programmed to record sound anywhere at any time in the absence of a human observer. They are also unlikely to disrupt the natural behavior of owls which means they can provide a more realistic assessment of habitat use in the area of interest. Furthermore, acoustic data collected with ARUs can be used to estimate population density without requiring physical capture of individuals through an acoustic spatial capture-recapture approach (SCR; Borchers and Efford 2008, Efford 2004, Efford et al. 2009a, 2009b). This approach involves "captures" occurring in the form of detected calls and "recaptures" as nearly simultaneous detections across multiple ARUs acting as proximity detectors within a trapping array. In addition, the acoustic data contains information on the signal strength (i.e., loudness) of detected calls which allows greater precision in estimating the location of individuals and the detection function (Dawson and Efford 2009).

Acoustic SCR has been used to estimate the population density of various taxa (i.e., cetaceans, primates, and frogs; Harris et al. 2013, Marques et al. 2013, Kidney et al. 2016, Measey et al. 2017), but only one published study has demonstrated its use with avian species (Ovenbirds *Seiurus aurocapilla*; Dawson and Efford 2009) since it was first introduced. Besides the advantages acoustic SCR offers for detecting elusive species, there is evidence that suggests acoustic estimates may be more precise than estimates from traditional methods, such as point counts and mist-netting (Dawson and Efford 2009, Pérez-Granados and Traba 2021). Though a requirement of the SCR method is the ability to distinguish individuals by their calls, which adds extensive processing time to analysis, it is possible for many owl species possessing individually distinct call characteristics (e.g., Eastern Screech-Owl (*Megascops asio*), Cavanaugh and Ritchison 1987, Nagy and Rockwell 2012; Barred Owl (*Strix varia*), Freeman 2000; Great Horned Owl (*Bubo virginianus*), Odom et. al 2013; Ural Owl (*Strix uralensis*), Zhou et al. 2020). Owls possess additional traits that appear to make them well suited for population monitoring with acoustic SCR, such as their frequent vocalizations produced by both sexes at low frequencies traveling long distances. Individuals can also be recorded in relatively stationary positions over the course of a nightly survey, meeting an additional assumption of the model, as they typically vocalize on or near the nest site during the breeding season (Bent 1961).

In this study, we addressed the lack of reliable population information available on owls by estimating the population density of species occurring in a protected park in north Georgia. Our specific objectives were: 1) to assess whether acoustic SCR can be used as a reliable monitoring technique for owl populations and 2) provide estimates of species density to increase our knowledge of understudied populations in Georgia. Application of acoustic SCR is necessary to further assess its viability as a technique for estimating owl populations. A reliable monitoring technique that avoids the limitations of traditional methods would not only increase our understanding of owl population dynamics but allow us to identify potential species at risk. Our methods can also be applied to other cryptic species in need of assessment.

Methods

Study Area

This study took place in the Chattahoochee River National Recreation Area (CRNRA), a 4,000-ha park extending 48 miles along the Chattahoochee River between the city of Atlanta, Georgia to the south and Lake Lanier to the north. Land cover here includes uplands with mixed pine and hardwood communities composed of predominantly tulip-poplar (*Liriodendron tulipifera*), American beech (*Fagus grandiflora*), oak (*Quercus spp.*), loblolly pine (*Pinus taeda*), and shortleaf pine (*Pinus echinata*) as well as lowland floodplains and riparian areas dominated by canopy species, such as river birch (*Betula nigra*) and green ash (*Fraxinus pennsylvanica*) (Byrne et al. 2014). Much of the area surrounding the park has high intensity urban land cover (i.e., central business districts, multi-family dwellings, commercial, industrial, and institutional facilities) especially where the river nears Atlanta (Figure 1.1).

Site Selection

Sites were selected primarily at random but constrained to areas greater than 30 meters from trails or roads containing suitable habitat for owls based on aerial photographs and 2019 National Land Cover Database (NLCD) maps. We generally distributed sites throughout the study area to maximize the spatial coverage of sampling. We surveyed 17 sites in 2020 and 18 sites in 2021 (Figure 2.1). At each site, we set up an array of 4 autonomous recording units (ARUs) each separated approximately 100 m apart (Figure 2.2). This distance was chosen to avoid detections occurring across all 4 microphones, which hinders inference on the location of calling individuals. We secured ARUs to trees with a diameter equal or smaller than the width of the ARU at a height of approximately 2 m. Precise locations of ARUs (~1 m) were recorded using a Trimble Juno handheld GPS unit.

Acoustic surveys

We used a combination of Song Meter SM2, SM2+, and SM3 recorders (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) to conduct passive acoustic surveys for owls. Each ARU and both attached omnidirectional microphones were tested prior to deployment. We programmed ARUs to record from February 1 through March 31 in 2020 and from February 1 through May 28 in 2021 to capture periods of the breeding season when owls are predicted to be most vocally active. ARUs recorded at 8 kHz in mono format every other night for nine hours between 18:00 and 07:00. We set two, two-hour breaks to occur during this time period to conserve battery power and prolong sampling. Microphone gain was set to 0 dB and recording files were stored in .wav format.

Acoustic analysis

We processed acoustic recordings using Kaleidoscope Pro 5 software (Wildlife Acoustics, Inc. 2021) to detect vocalizations of Barred Owls, Great Horned Owls, and Eastern Screech-Owls. Recordings were scanned with a fast Fourier transform (FFT) window size of 10.67 ms, and detections were extracted based on a set of specified parameters describing the typical frequency range and duration of owl calls (i.e., 100-800 Hz, 0.2-15 s). We manually listened to each detected signal while also viewing the spectrogram to distinguish vocalizing species of interest from background noise on the recordings.

We measured the signal strength (dB) of each detected owl vocalization in Raven Pro 1.6.1 (K. Lisa Yang Center for Conservation Bioacoustics, 2019). Spectrograms were first configured using the following settings: Hann window function, 3 dB filter bandwidth of 59.9 Hz, and 90% overlap, resulting in a grid resolution of 4096 DFT and 3.91 Hz. This DFT size provides high frequency resolution relative to time resolution, thus allowing for more precise frequency measurements (Charif et al. 2010). Odom et al. (2013) used similar spectrogram settings in their analysis of Great Horned Owl calls, to which we made slight modifications to improve spectrogram appearance. We then positioned a time-frequency window on the spectrogram of the call to measure the average power density. For Great Horned Owl calls, this window was 2 seconds x 150 Hz placed at 200-350 Hz for males and 250-400 Hz for females. For Barred Owl calls, the window was the length of the call, which varied from 1-2 seconds, x 300 Hz, placed at 300-600 Hz for males and 400-700 Hz for females. For Screech-Owl calls, the window was 2 seconds x 200 Hz placed at 500-700 Hz for males and 600-800 Hz for females. After measuring each call, we measured the ambient noise in the recording by placing a window of the same length and frequency range within 0.5 seconds of the call. Our final measurement of signal strength (S') accounting for background noise was obtained using the formula described by Dawson and Efford (2009),

$$S' = 10\log_{10}(10^{S/10} - 10^{N/10}),$$

where S is the call measurement and N is the noise measurement in decibels.

Individual identification

To determine the number of calling individuals that were detected, we first classified calls based on sex. Female Great Horned Owl calls can be distinguished from males by the number of notes and frequency range. In the species-typical territorial hoot, females produce two to four short notes followed by two to three long notes, whereas males produce one to two short notes followed by two to three long notes. Female hoots are higher-pitched, often above 400 Hz, while male hoots typically stay below this frequency (Emlen 1973, Houston et al. 1998, Kinstler 2009, Odom et al. 2013). Female Barred Owl calls are also higher-pitched than males at or above 600 Hz, and the terminal notes of female calls are longer (~0.8 s vs. 0.4 s) with more inflection points (Odom 2009). Similarly, the "bounce" songs of female Screech-Owls are approximately 100 Hz higher on average than those of males, and they include more notes produced at a slower rate (Cavanagh and Ritchison 1987). Based on these characteristics, male and female calls were distinguished by manually viewing call spectrograms.

For each species, we developed two sets of representative calls (1 male, 1 female) from each individual bout of calls to be subjected to further analysis. Great Horned Owl calls included the individually distinct, species-typical territorial hoot consisting of 3-6 notes (Houston et al. 1998; Odom et al. 2013; Figure 2.3a). For Barred Owls, we only included the final four notes of the Legato hoot known to exhibit less variability within individuals than between (Freeman 2000; Figure 2.3b). Screech-Owl calls included the territorial ‘bounce’ call which has been successfully used for individual discrimination of a small population of owls (Nagy and Rockwell 2012; Figure 2.3c).

We conducted spectrogram cross-correlations (SPCC) on each set of male and female calls from each species using the batch correlator tool in Raven Pro. SPCC provides a time-frequency assessment of similarity between two call spectrograms, the output of which is a matrix of peak correlation values from 0 to 1 for each pair (Charif et al 2010). A band pass filter was set to exclude background noise outside the frequency band of calls to reduce its effect on correlation values. We selected the default settings for normalization and spectrogram power values on the linear scale.

By subtracting all correlation values from 1, each correlation matrix was converted to a dissimilarity matrix to be entered into a hierarchical clustering analysis in R (R Core Team 2021). Hierarchical clustering is an agglomerative “bottom-up” approach which begins with each call separated into its own cluster and proceeds by successively joining the closest pairs of clusters (Liu et al 2012). Out of several agglomeration methods that can be used (e.g., single, average, complete), average linkage was chosen for all clustering analyses, because it produced the highest cophenetic correlations. This value quantifies the quality of clustering as it describes how well the patterns of dissimilarities are represented (Liu et al 2012). Average linkage tends to be the best option for most datasets, as it defines the distance between clusters based on the average of all distances between pairs of observations, and therefore minimizes within-cluster variance (Yim and Ramdeen 2015).

To determine the correct number of clusters and evaluate their validity, we chose to use the Calinski-Harabasz index. The highest Calinski-Harabasz index value indicates the correct number of clusters based on the average between-cluster and within-cluster variances (Calinski and Harabasz 1974, Li et al 2020). We further evaluated clusters based on evidence from the data of calls being produced by the same individual (i.e., detected at the same time on multiple recorders). If the clustering algorithm separated these calls into multiple clusters, we joined them together. Similarly, we made decisions to separate or join clusters considering estimated breeding home range size of owls that made some calls unlikely to be from the same individual if detected at recorders spaced a wider distance than the diameter of the largest known home range. Finally, we manually examined spectrograms of clustered calls to confirm they possessed similar characteristics and there were no obvious misclassifications.

Statistical analysis

We used methodology developed by Stevenson et al. (2021) to estimate population density (individuals per ha) of owls. These methods stem from earlier acoustic SCR methods (Borchers et al. 2015, Dawson and Efford 2009, Efford et al. 2009, Stevenson et al. 2015) but distinctively allow for direct estimation of the detection function, call rate, and animal density from acoustic data. Specification of a new likelihood constructed under the assumption of dependent call locations also allows for the use of likelihood-based tools such as AIC. An additional assumption is that animals' locations are a realization of an inhomogeneous Poisson process across the survey region (Borchers and Efford 2008, Stevenson et al. 2021). Animal density is modeled via a loglinear relationship

$$\log\{D(s)\} = \beta_0 + \beta_1 x_1(s) + \beta_2 x_2(s) + \ldots,$$

where D(s) is animal density at location s, $x_q(s)$ is the value of a spatial covariate measured at location s, and $\beta = (\beta_0, \ldots, \beta_Q)$ are estimated coefficients characterizing spatially varying density (Stevenson et al. 2021). The model suggests that $n \sim \text{Poisson}\{\int_S D(s)ds\}$ where n is the total number of animals in the entire survey region, S (Borchers et al. 2015).

The observation model differs from other SCR models, because ARUs are considered "signal-strength proximity detectors" (Efford et. al 2009). We assume that signal-strength S decreases with distance d from the call source to the ARU. Sound attenuation can be modeled by:

$$S(\mathbf{x}, \mathbf{u}) = \alpha_0 + \alpha_1 d(\mathbf{x}, \mathbf{u}) + \epsilon,$$

where $\epsilon \sim \text{Normal}(0, \sigma_s^2)$ and $\mathbf{u}$ is the location of a signal detected by an ARU at location $\mathbf{x}$. Fitting the model in R produces estimates of α_0, α_1, and σ_s^2; we abbreviate these parameters by $\boldsymbol{\theta}$. A detection is defined as a signal with a strength exceeding an arbitrary threshold c, below which sounds are considered background noise. The probability $\Pr(S_{ij} < c)$ is a function of $\boldsymbol{\theta}$, $\mathbf{u}$, and $\mathbf{x}$. If we identify the function by $\gamma(\boldsymbol{\theta}, \mathbf{x}, \mathbf{u})$, then the observation model is:

$$p_{ij} = 1 - \Phi(\gamma(\boldsymbol{\theta}, \mathbf{x}, \mathbf{u}))$$

$$y_{ij} \sim \text{Bernoulli}(p_{ij}),$$

where Φ() represents the normal cumulative distribution function (Royle et al. 2013).

We fitted acoustic SCR models using the R package *ascr* (Stevenson 2021). Our data consists of an observed capture history for each call representing the microphones it was detected by as well as the measured signal strength (dB). Data was pooled across both surveys and the effect of ‘year’ on density was included in the models. Incorporating signal strength information requires specification of an arbitrary threshold *c*, below which signals are considered background noise and ignored. We defined a detected signal as one with a signal strength greater than 35 dB. Parameters to be estimated by our models include animal density (D), call rate (λ), source strength (β_0), the rate of sound attenuation (β_1), and the standard deviation of measured signal strengths (σ_S) (Dawson and Efford 2009, Stevenson et al. 2021).

Results

Data Summary

Our acoustic surveys captured a combined total of 31,410 hours of recordings at 29 sampling locations. All three owl species were detected during both survey years. Barred Owls were detected most frequently with 6,000 detections at 100% of sites in 2020 and 7,938 detections at 100% of sites in 2021. Great Horned Owls had 615 detections at 47% of sites in 2020 and 2,251 detections at 67% of sites in 2021. Eastern Screech-Owls were detected 130 times at 12% of sites in 2020 and 132 times at 6% of sites in 2021.

In 2020 and 2021, respectively, 9 (13%) and 23 (32%) ARUs failed to complete their recording schedule. When the cause of data loss could be identified, it was most often due to damage incurred from moisture or wildlife disturbance. There was only one case in which disturbance by humans was apparent in 2021.

Great Horned Owl

We developed a set of 113 representative male great horned owl calls and a set of 89 representative female calls from both sampling years to be entered into hierarchical clustering analysis. The optimal number of clusters (i.e., individuals) based on the Calinski-Harbasz Index was 5 males and 5 females. However, we made decisions to manually separate some clusters further using prior knowledge of characteristics that made certain calls highly unlikely to be from the same individual. For example, a cluster contained calls from males detected at sample locations over 38 km apart, a distance over 10 times wider than the diameter of the largest estimated territory used by a Great Horned Owl (i.e., 883 ha; Houston et al. 1998). We determined the final number of clusters to be 7 males and 6 females. For both sexes, this number of clusters gives the second-highest Calinkski-Harbasz index value (Figure 2.4). In addition, the average silhouette widths of male and female clusters are both greater than 0, and the average distance between clusters is greater than within clusters; therefore, there is no indication of poor clustering performance (Table 2.1).

In developing our acoustic SCR model of Great Horned Owl density, we encountered numerical issues upon inclusion of measured signal strengths that led us to conclude our data was likely not well suited to assumptions of the signal strength detection function, such as the spherical spreading of sound. For this reason, we decided to use the hazard halfnormal function in place of the signal strength detection function, as we felt our model was robust to the incorporation of signal strength data. It provided estimates of animal density and call rate with good precision: $\hat{D} = 0.002$ (95% CI = 0.001, 0.003) individuals per hectare and $\mu = 3.51$ (95% CI = 3.47, 3.56) calls per night. Based on model estimates of λ_0 and σ (Table 2.2), Great Horned Owls may be detected at distances up to 240 m from recorders (Figure 2.5). The detection function allows us to estimate the effective sampling area of our surveys was 757.1 ± 2.8 ha. Extrapolating density to the total area of the CRNRA (4,269 ha) yields an estimated population of 8 (95% CI = 4, 13) individuals.

Barred Owl

We developed a set of 80 representative male Barred Owl calls detected during the first sampling year to be entered into hierarchical clustering analysis. Based on the Calinski-Harabasz index, the optimal number of clusters was 3. There was not a clear pattern of separation between clusters, with many clustered calls varying substantially in frequency and duration as well as the sampling locations at which they were detected. We attempted to manually separate clusters further, but the number of clusters we identified held one of the lowest Calinski-Harbasz index values of all possible clusters and an average silhouette width close to 0, indicating cluster overlap. As a result, we decided the correct number of clusters could not be determined reliably for Barred Owls and instead estimated call density ($\hat{D}$) as opposed to animal density.

The acoustic SCR model incorporating measured signal strengths estimated $\hat{D} = 0.004$ (95% CI = 0.004, 0.005) Barred Owl calls per hectare per hour. Additional estimates, standard errors, and 95% CIs for parameters describing the estimated call detection function are reported in Table 2.3. According to the model, the average Barred Owl call is 87.2 (95% CI = 86.6, 87.9) dB and attenuates in the environment at a rate of 0.046 (95% CI = 0.045, 0.047) dB/m, suggesting individuals can be detected up to 2,000 m away (Figure 2.6). The area effectively sampled over both survey years is an estimated 12,277.5 ± 19.0 ha.

In comparison, a model using the hazard halfnormal detection function without measured signal strengths offered slightly greater precision and a larger estimate of $\hat{D} = 0.020$ (95% CI = 0.019, 0.022) calls per hectare per hour. The model estimated the detection function parameters, λ_0 and σ, with similar precision to those estimated by the signal strength model (Table 2.3). However, the detection function itself differed greatly, estimating detection probability of Barred Owls reaches near 0 at 580 m, approximately ¼ the distance estimated by the signal strength model (Figure 2.6). Accordingly, the model estimates a smaller effective sampling area of 2,390.9 ± 5.1 ha.

Eastern Screech-Owl

We detected 6 bouts of Eastern Screech-Owl calls, 5 of which were identified as male and 1 as female based on differences in average call frequency (female calls are ~100 Hz higher). Due to the lack of representative calls and overall detections, we deemed hierarchical clustering of calls unproductive in this case and resorted to estimating call density assuming that our low capture success would not allow reliable estimation of animal density.

The acoustic SCR model of Screech-Owl call density incorporating measured signal strengths showed a lack of convergence which may be attributed to small sample size. We thus decided again that our data would be better suited to model using the hazard halfnormal detection function. The model provided an estimated call density of $\hat{D}$ = 0.007 (95% CI = 0.005, 0.010) calls per hectare per hour. Based on estimated λ_0 and σ (Table 2.4), the call detection function suggests Screech-Owls can be detected up to a distance of 120 m (Figure 2.7). We estimate the area effectively sampled for Screech-Owls in our study was 201.5 ± 2.0 ha.

Discussion

We explored the utility of autonomous recording units for estimating owl populations and discovered some advantages and limitations. We successfully detected three species of interest known to persist in our study area, though species differed greatly in their detection frequency. Individual discrimination via SPCC and hierarchical clustering analyses yielded encouraging results for Great Horned Owls which allowed us to estimate population density across the CRNRA using acoustic SCR. Due to poor clustering performance and an insufficient number of detections, respectively, we could not estimate population density of Barred Owls or Eastern

Screech-Owls and resorted to estimating the density of calls. Comparison of models with and without signal strength data resulted in the unexpected finding that the additional information on call location did not increase precision of the density estimate.

SPCC and hierarchical clustering of calls was an imperfect process but provided valid results when combined with visual comparison of spectrograms and prior knowledge of territory size and the locations of detected calls. We had the most success using this method to discriminate individual Great Horned Owls, as the number determined by hierarchical clustering only differed by 1 from the number we determined by manual clustering. SPCC is sensitive to recording quality and background noise which may have caused the incorrect classification of some calls. We attempted to avoid this by filtering out noise below and above the frequency band of calls, but it was not possible to exclude noise occurring at the same frequency. Nevertheless, some studies have had success using low quality recordings to reliably discriminate individuals of other bird species using only SPCC (e.g., Ovenbirds *Seiurus aurocapilla*, Ehnes and Foote 2015).

It is reasonable to suggest the discrimination performance of SPCC may depend on the species, performing best on those that possess more individually distinct call characteristics. This could explain why we had such little success discriminating individual Barred Owls. Out of 13 types of vocalizations they produce, only one – the legato hoot – has been investigated and found to be individually distinct based on discriminant function analysis (DFA) and visual discrimination by human observers (Freeman 2000). DFA requires that the number of individuals are known before classification so is not useful in the context of estimating populations (Terry et al. 2001, Terry et al. 2005). It may be that the legato hoot does not possess the characteristics necessary for correct classification by SPCC and is better suited to visual classification, though this method on its own introduces a greater degree of subjectivity. Such appears to be the case for calls of the Tawny Owl (*Strix aluco*), which can be reliably classified by manual viewing, but not using multivariate techniques, including SPCC (Peri 2018).

The performance of SPCC also can be affected by the population size being monitored. Discrimination success is found to be lower for larger populations under consideration, and many studies investigating the individual distinctiveness of calls, including Barred Owls', involved less than 20 individuals (Linhart and Salek 2017). It is plausible we detected at least this many individuals considering the average breeding home range size of Barred Owls and the estimated sampling area of recorders, and this may have decreased the performance of SPCC. Furthermore, discrimination performance is affected by the number of calls available per individual. Including a greater number of calls per individual increases the performance of SPCC and the size of the population that can be reliably distinguished (Linhart and Salek 2017). We cannot be certain whether we captured a sufficient number of calls per individual, but this could be ensured by increasing the recording effort at sites with less frequent detections by extending the survey period or deploying additional ARUs in a sampling array.

Our estimate of Great Horned Owl density in the CRNRA is comparable to census estimates in other parts of the U.S., though there are few available. In North Dakota, Igl and Johnson (1997) detected 18 individuals on approximately 8000 ha, which is equivalent to 0.0022 individuals/ha and falls within the confidence interval of our estimate. Interestingly, the number of individuals we detected in our surveys (13) is greater than the model's estimate of abundance in the CRNRA, but equal to the upper limit. It seems unlikely that we detected all individuals present considering we sampled an estimated 18% of the study area at most, but it's not impossible considering male territories can span well over 800 ha and are completely defended from intruders (Houston et al. 1998).

Though our model's density estimate appears reasonable, it lacks the precision obtained by Stevenson et al. (2021) in their introduction of the cue rate model applied to an anuran species. This is likely due to the fact that we were unable to collect data on the time-of-arrival (TOA) of calls, which provides additional information on call locations and significantly increases the precision of acoustic SCR models (Borchers et al. 2015, Stevenson et al. 2015). Collection of TOA data requires equipment capable of synchronizing all recorders to the same clock so that minuscule differences in received signal times can be measured (in milliseconds). A study of the Cape peninsula moss frog *Arthroleptella lightfooti* accomplished this using an array of six microphones spaced ≤ 5 m apart connected to a central clock (Measey et al. 2017). This design was not feasible in our case as arrays required much larger spacing to avoid detections occurring across all microphones considering the loudness of owl vocalizations. Certain technology exists that could have solved our issue; an external GPS accessory available from Wildlife Acoustics can be applied to SM2 and SM3 recorders to maintain precise time synchronization, but each recorder requires its own accessory. Acquiring this amount of equipment was not within our budget, but it could be a cost-effective option for smaller-scale studies using fewer recorders. It is worth noting that, despite our lack of TOA data, the additional parameters of the model, μ, λ_0, and σ, were estimated with similar or greater precision than previous studies (e.g., Stevenson et al. 2021).

Comparing models of Barred Owl call density yielded unexpected results. We hypothesized that information on measured signal strengths would improve inference about the location of call sources and thus increase precision of the density estimate, which was originally demonstrated by Dawson and Efford (2009), but this was not the case. More recently, it was found that signal strengths provide near nominal information on animal location compared to TOA data (Stevenson et al. 2015). In the case of *A. lightfooti*, models actually performed better in the absence of signal strengths, so they were excluded (B. C. Stevenson, personal communication, 14 Feb 2022). Our results are consistent with this finding, and future research should focus effort on obtaining TOA data to assess its effect on model performance in acoustic studies of owls.

Nondetection of Screech-Owls at the majority of sites in our study (i.e., 90%) may best be explained by the presence of larger owl species. It has been suggested that Screech-Owls vocalize less frequently where Barred and Great Horned Owls are present to avoid predation. At least one, and more often both, larger species were present at sites where Screech-Owls were detected, which is consistent with findings of a study of Screech-Owls in suburban parks of New York City (Nagy and Rockwell 2013). Interestingly, this study had another finding similar to ours, in which some sites where Screech-Owls were detected did not have any detections in subsequent years, suggesting that these populations are not stable. Previous studies of Eastern Screech-Owls focusing on occupancy assessments had greater success detecting individuals using call broadcast surveys compared to our use of ARUs (e.g., Nagy and Rockwell 2013, Leonard et al. 2015). We suggest that ARUs on their own are not an effective monitoring tool for Eastern Screech-Owls, but future study designs could benefit from combining the two survey methods. An additional recommendation is to increase the density of ARUs and decrease the spacing within arrays, as our chosen spacing of 100 m was apparently too large to detect most calls on more than one ARU. Our estimated detection function supports this finding, suggesting detection probability decreases significantly for calls produced between 50-100 m from an ARU.

Conclusion

Our study shows that acoustic SCR can be an effective technique for estimating populations of owl species. Although it requires the ability to distinguish detected individuals by their calls, we have demonstrated a method for doing so using SPCC in combination with hierarchical and manual clustering analyses. This method contains a level of subjectivity that is difficult to quantify and may need fine-tuning, but at present it appears to be a valid tool at least for monitoring Great Horned Owls. With further research on vocal individuality, we expect it will prove useful for individual discrimination within other owl species.

In this study, acoustic SCR methods offered advantages over traditional monitoring techniques, considering the technology and equipment available to us and certain limitations of our study area. However, the benefits and cost-effectiveness of implementing acoustic SCR will likely vary between studies. The current cost of purchasing and maintaining a large inventory of recording equipment may be unfeasible compared to the cost of employing personnel to conduct point count surveys or constant effort mist-netting. Although acoustic methods require comparatively little field effort, analysis of acoustic data can present challenges with extensive processing times and the need for highly trained personnel. Nevertheless, acoustic methods enable researchers to study areas that are restricted or difficult to access during survey periods of interest, which was a major limiting factor of our study.

We emphasize the importance of survey design for future studies adopting an acoustic SCR framework to monitor species of interest. Different species will likely benefit from different recording efforts depending on ecological traits such as vocalization frequency. Special consideration should be given to determining the optimal number and spatial arrangement of detectors to obtain sufficient detections, and preliminary field tests are encouraged before conducting large scale studies. Studies should also be designed to collect TOA data when feasible to obtain the most precise estimates of animal location and density. Acoustic SCR is a useful method for monitoring cryptic bird species, and it should be applied to other taxa that are traditionally difficult to monitor. In the case of owls, we can conclude its utility extends well beyond traditional techniques that have been unsuited to provide reliable population estimates. Furthermore, acoustic SCR offers the advantages of being non-invasive and reproducible with limited personnel making it easy to incorporate into existing monitoring programs to increase our understanding of population dynamics and improve conservation strategies.

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Table 2.1. Cluster statistics describing the validity of Great Horned Owl clusters determined optimal using the Calinski-Harbasz Index (CH). The average silhouette width measures how well calls are clustered on a scale of -1 to 1 based on the estimated distance between and within clusters.

	No. of clusters	CH	Silhouette width	Distance between	Distance within
Male	7	15.681	0.131	0.568	0.434
Female	6	16.253	0.149	0.574	0.428

Table 2.2. Acoustic SCR estimates of Great Horned Owl density with standard errors and 95% confidence intervals (CI). *D* is reported in animals/ha with Intercept and year effect estimates indicated in parentheses. σ is reported in m and μ in calls/night.

Parameter	Estimate	SE	95% CI
D(Int)	0.002	0.175	(0.001, 0.003)
D(year)	0.322	0.206	(-0.081, 0.726)
λ_0	2.559	0.056	(2.449, 2.668)
σ	4.035	0.012	(4.012, 4.058)
μ	3.514	0.021	(3.472, 3.556)

Table 2.3. Compared acoustic SCR estimates of Barred Owl call density with standard errors and 95% confidence intervals (CI) from models with and without signal strength (SS) data. Call density (*D*) is reported in calls/ha/hour, source signal strength (β_0) and standard deviation (σ_s) in dB, and sound attenuation (β_1) in dB/m.

Parameter	SS		Without SS	
	Estimate (95% CI)	SE	Estimate (95% CI)	SE
D(Int)	0.004 (0.004, 0.005)	0.029	0.020 (0.019, 0.022)	0.037
D(year)	0.137 (0.102, 0.171)	0.018	0.229 (0.196, 0.262)	0.017
β_0	87.231 (86.616, 87.846)	0.314		
β_1	0.046 (0.045, 0.047)	4.1×10^{-4}		
λ_0			15.423 (14.208, 16.638)	0.620
σ	15.711 (15.568, 15.854)	0.073	145.792 (142.058, 149.526)	1.905

Table 2.4. Acoustic SCR estimates of Eastern Screech-Owl call density with standard errors and 95% confidence intervals (CI). *D* is reported in calls/ha/hour and σ in m.

Parameter	Estimate	SE	95% CI
D(Int)	0.007	0.207	(0.005, 0.010)
D(year)	-0.046	0.124	(-0.288, 0.196)
λ_0	17.822	8.486	(1.190, 34.453)
σ	29.319	2.995	(23.448, 35.189)

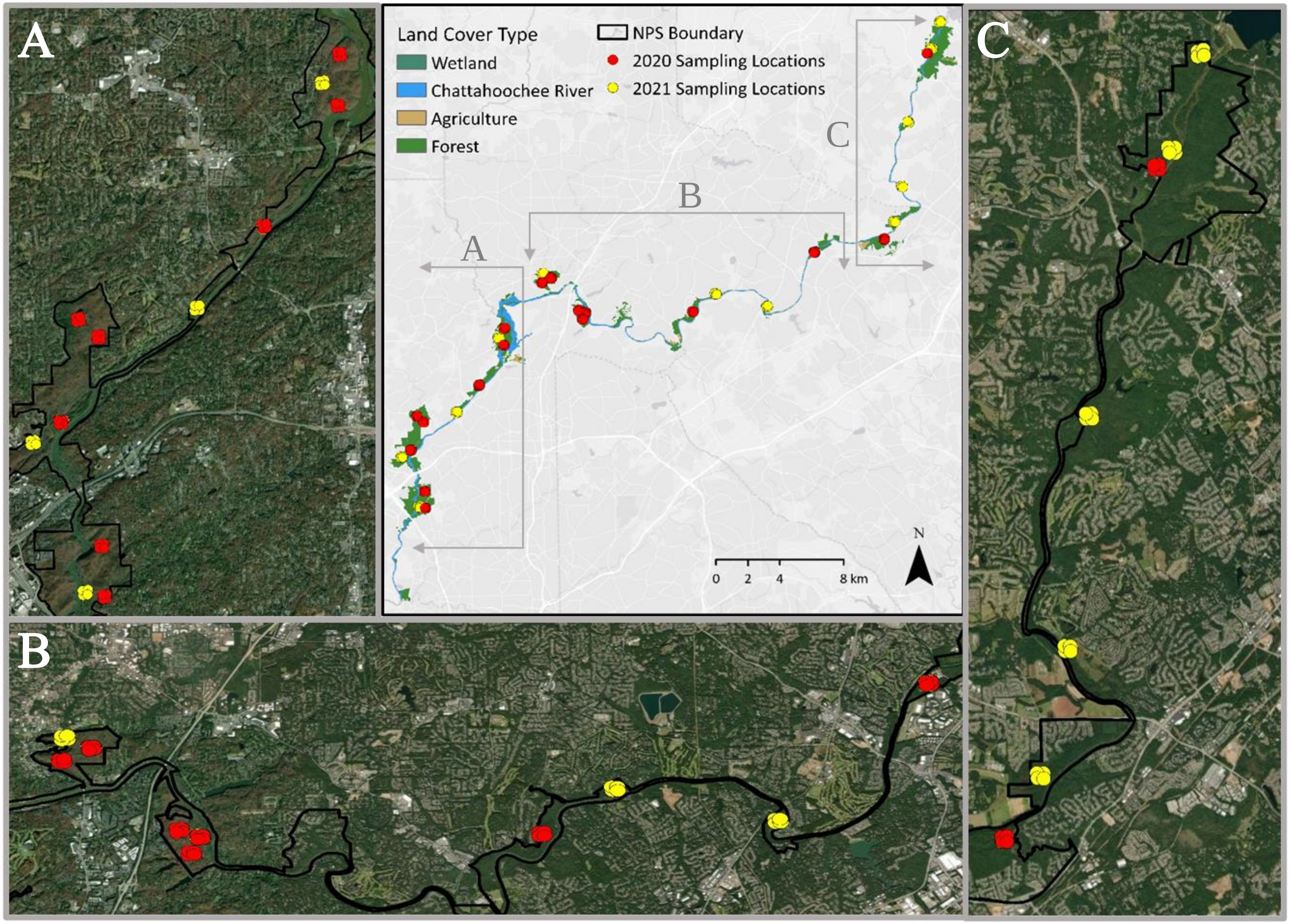

Figure 2.1. Locations of acoustic sampling arrays deployed during the 2020-2021 breeding seasons in the Chattahoochee River National Recreation Area with aerial imagery on inset maps showing land cover surrounding sampling locations.

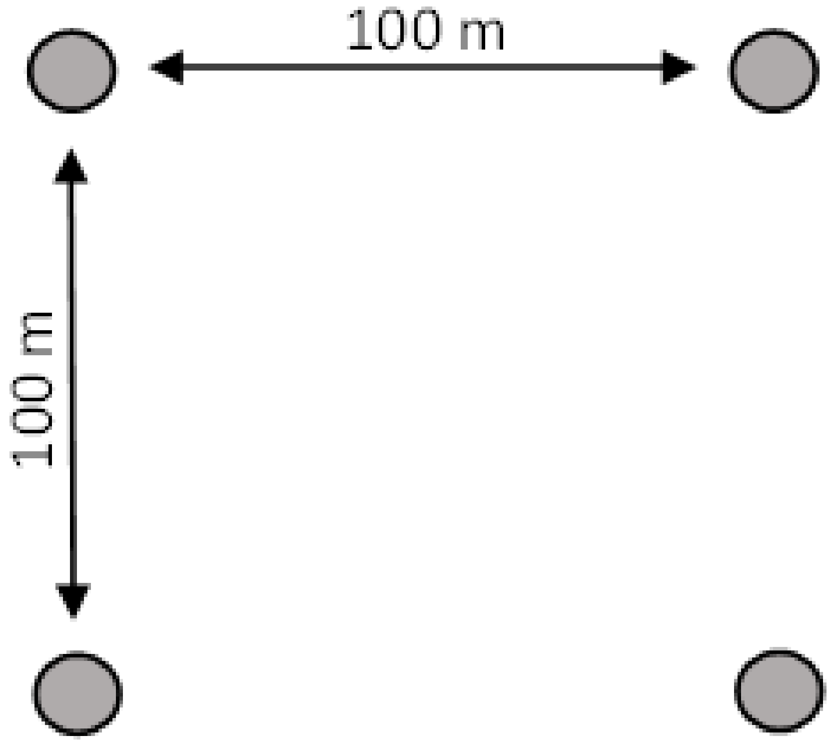

Figure 2.2. Example autonomous recording unit (ARU) configuration within a sampling array. Arrays were deployed at 17 sites in 2020 and 18 sites in 2021.

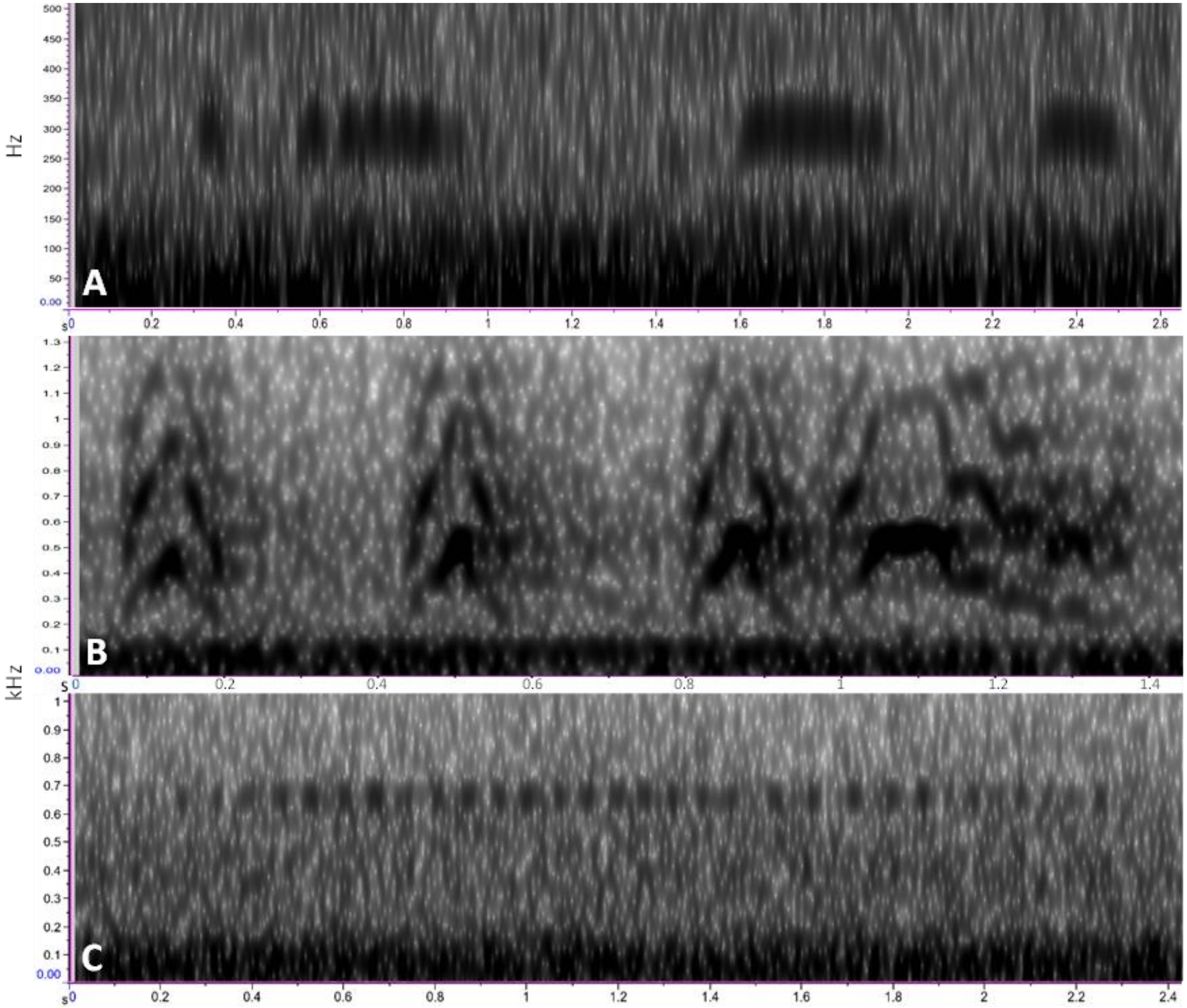

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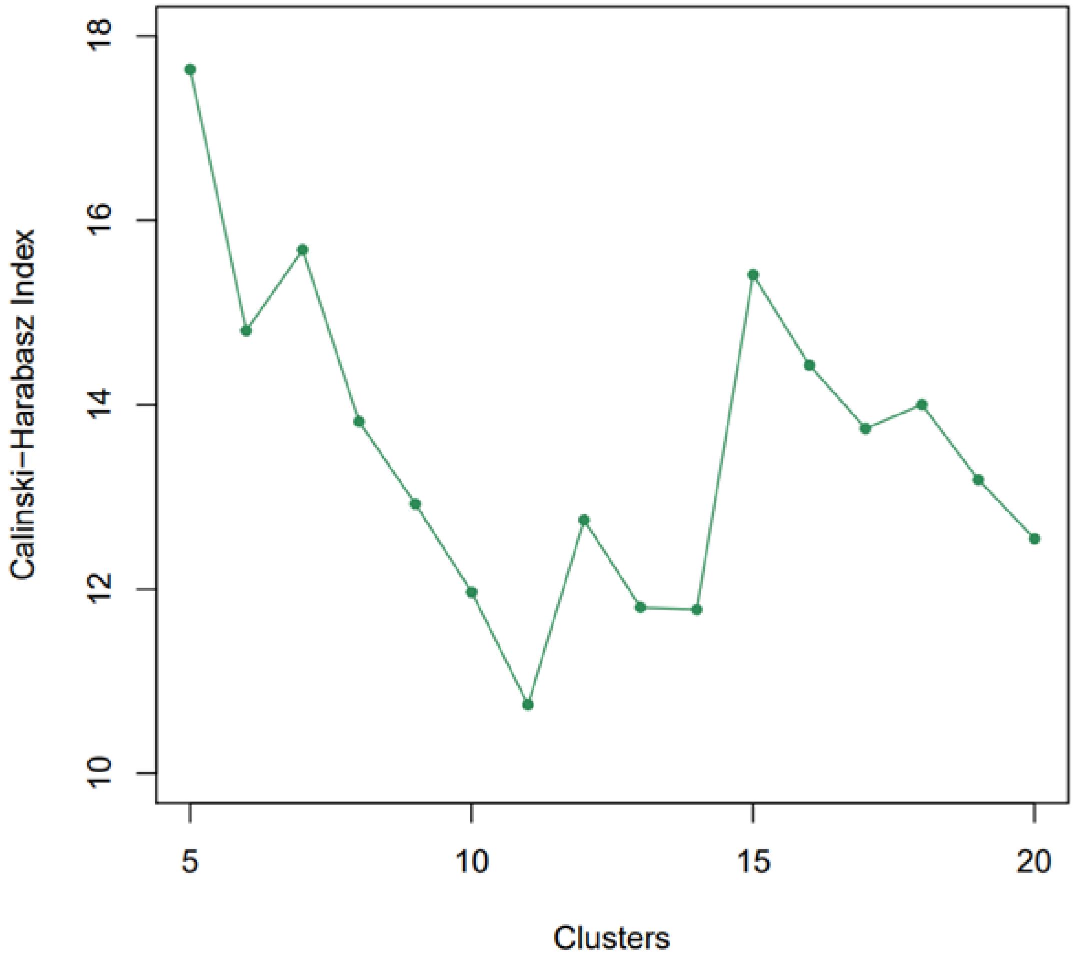
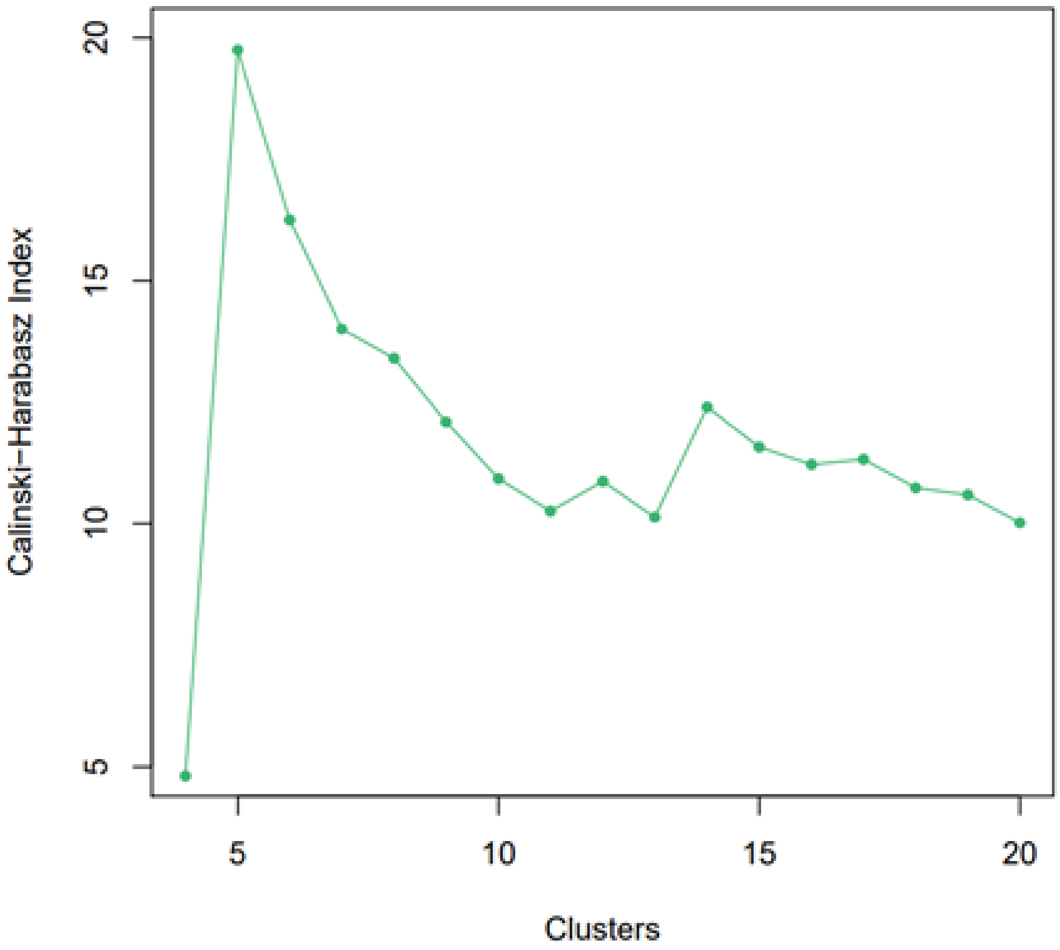
Figure 2.3. Types of vocalizations used in individual discrimination of owl species. Spectrogram A shows the territorial hoot of a Great Horned Owl. Spectrogram B shows the legato hoot of a Barred Owl. Spectrogram C shows the bounce call of an Eastern Screech-Owl. Calls shown are from males of each species; females produce the same calls of longer duration at higher frequencies.



a).



b).

Figure 2.4. Calinski-Harabasz (CH) Index values associated with each possible number of clusters for a) male and b) female Great Horned Owl calls. Higher CH values indicate tighter clusters with lower variance within and greater separation from other clusters.

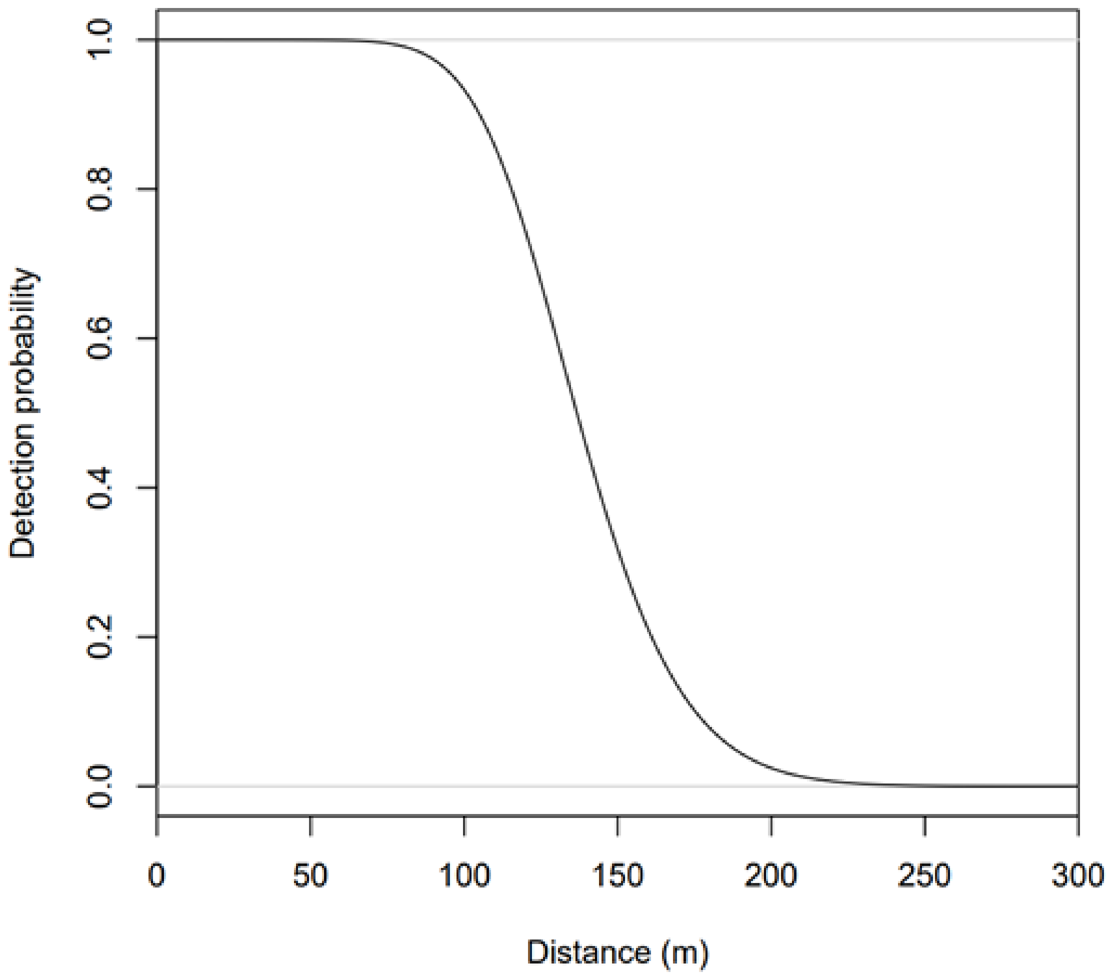


Figure 2.5. Estimated detection function from the acoustic SCR model of Great Horned Owl density.

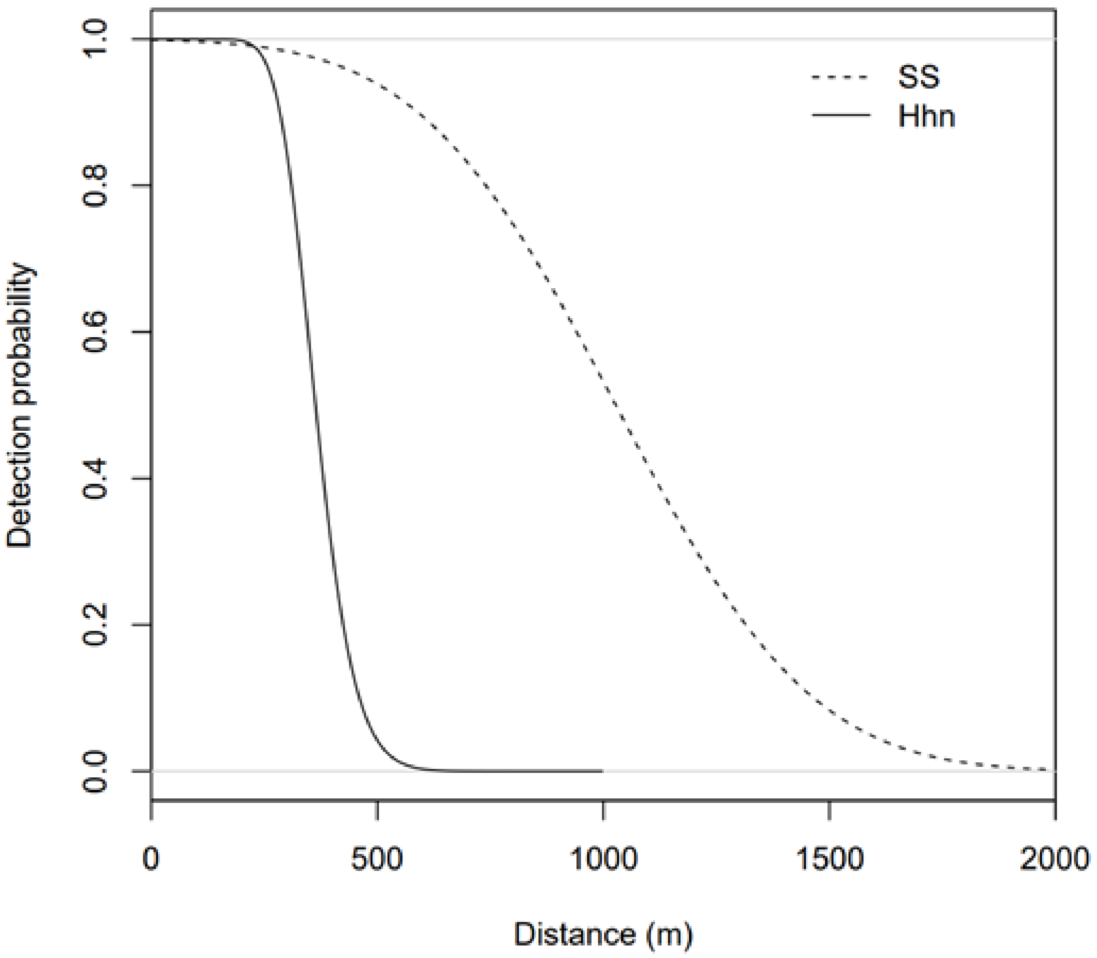


Figure 2.6. Estimated call detection functions from acoustic SCR models of Barred Owl call density with signal strength (SS) and hazard half-normal (Hhn) functions.

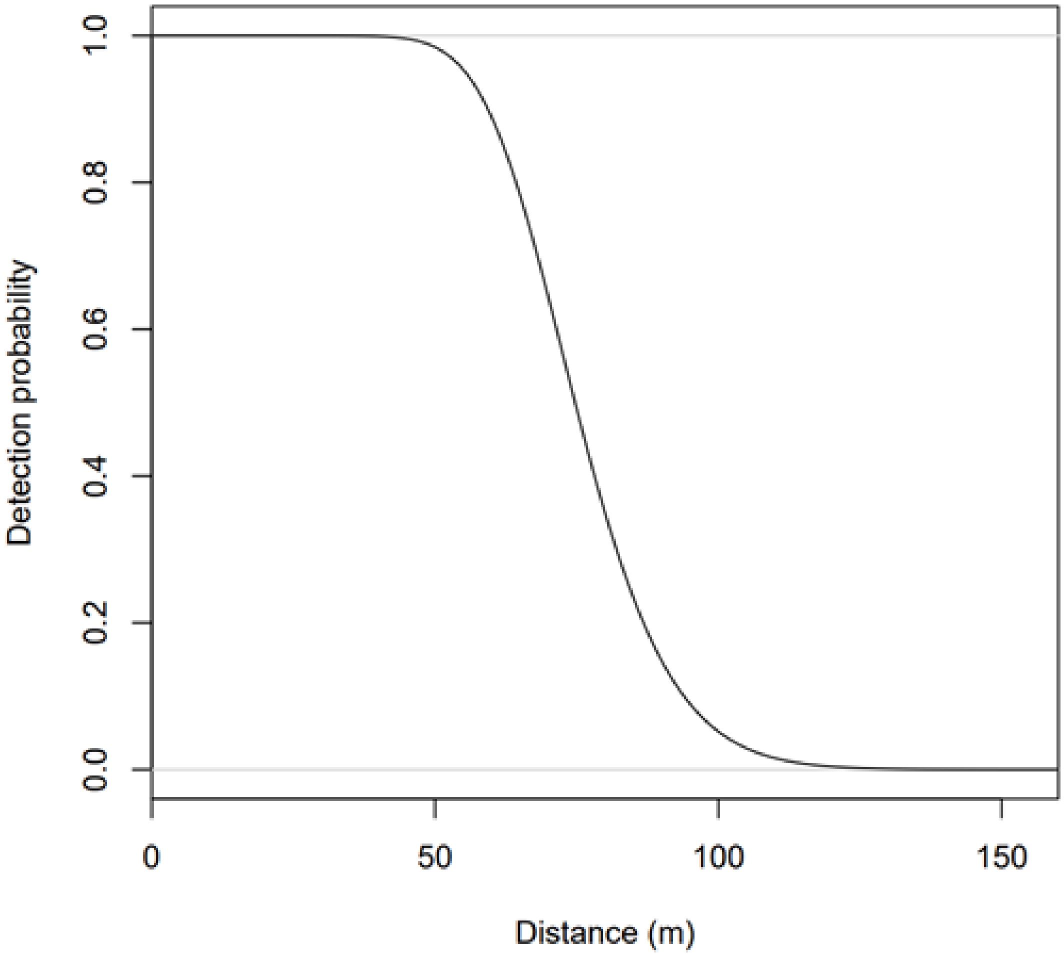


Figure 2.7. Estimated call detection function from the acoustic SCR model of Eastern Screech-Owl call density.

CHAPTER 3

THE INFLUENCE OF ANTHROPOGENIC FACTORS ON THE POPULATION DENSITY OF GREAT HORNED OWLS IN THE CHATTAHOOCHEE RIVER NATIONAL RECREATION AREA

[1] Martin, Lily H., J. Hepinstall-Cymerman, R. B. Chandler, and M. C. Parrish. To be submitted to *The Journal of Raptor Research*.

Abstract

Noise and light pollution are by-products of human development which may threaten avian populations, but their effects are not yet well understood. To investigate the influence of anthropogenic factors on Great Horned Owl density, we combine an acoustic dataset collected over two seasons in a protected park in Georgia with high resolution data on anthropogenic noise and artificial night lighting. We take a multi-scale approach to model selection to identify important variables explaining owl density at the local, home range, and landscape scale. Our models indicate significant effects of edge density and anthropogenic noise on Great Horned Owl density at the local scale. These findings add to the growing body of evidence indicating negative impacts of noise on wildlife and provide important management implications for populations of Great Horned Owls within highly urbanized areas.

Introduction

Anthropogenic noise and light pollution have continually increased in intensity and distribution over the past century alongside a rapidly growing human population and urbanizing landscape (Buxton et al. 2017). Recent efforts to evaluate the impacts of anthropogenic stressors on wildlife have produced a growing body of evidence indicating noise and artificial light are detrimental to natural communities (e.g., Hölker et al. 2010, Francis and Barber 2013, Shannon et al. 2016). For avian populations, the potential effects of noise include behavioral responses (e.g., stress, avoidance, changes in foraging), changes in reproductive timing and success, interference with vocal communication and perception of acoustic signals, and declines in abundance (Bayne et al. 2008, Ortega 2012, Pijanowski et al. 2011, Senzaki et al. 2020). Similarly, artificial light can cause shifts in temporal behavior due to alteration of circadian rhythms which are controlled by photoperiod (Dominoni 2015, Gaston et al. 2017). Light pollution also alters the way in which birds visually perceive their environment, and increased mortality due to collisions with man-made structures is commonly reported (Longcore et al. 2013).

Some species of birds are more susceptible to noise and light pollution than others depending on traits such as habitat association, diet, vocal frequency, and light-gathering ability of the eye (Senzaki et al. 2020). Several studies have focused on the impacts of anthropogenic noise on owls, as they are nocturnal predators that rely on acoustic signals to hunt. Hunting success of owls decreases with increasing noise levels, which may cause them to abandon areas of otherwise suitable habitat (Mason et al. 2016, Senzaki et al. 2016). There is evidence of reduced species richness and occupancy (e.g., Tawny Owl *Strix aluco*, Long-eared Owl *Asio otus*, Mottled Owl *Ciccaba virgata*) in urban areas with greater ambient noise intensity (Frohlich and Ciach 2017, 2018, Marín-Gómez et al. 2020). In natural habitats with dispersed industrial noise sources, however, the effect of noise on owls is suggested to be minimal (Shonfield and Bayne 2017). Correspondingly little is known on the impact of light pollution on owls with current studies reporting contrasting effects on species occurrence (Scobie et al. 2016, Marín-Gómez et al. 2020, Rodríguez et al. 2021). The influence of anthropogenic stressors on the abundance and spatial distributions of owl populations within highly urbanized areas remains understudied.

Many raptor species, including Great Horned Owls, Barred Owls, and Eastern Screech-Owls, have demonstrated an ability to adapt to and exploit areas under varying levels of human development. Some species have shown greater survival and reproductive rates in developed habitats owing to the greater availability of prey items and nesting sites (Kettel et al. 2018). Despite the benefits of urban habitat use, there are a number of mortality risks present that may cause these areas to function as "ecological traps" for raptors. Urban landscapes introduce a higher risk of collisions with man-made structures, exposure to chemical contaminants, disease transmission, and electrocution by overhead power structures (Dwyer et al. 2018). Nevertheless, the challenges faced by raptors differs between species; therefore, species specific responses to factors of urbanization must be understood for effective management of urban populations.

The characteristics that urban habitats must possess in order for owls to exploit them are not well understood, but it has been suggested that at some point urban intensity becomes too great for them to persist. For example, occupancy of Eastern Screech-Owls in urban parks of New York City declines sharply where impervious surfaces make up more than 50% of landcover (Nagy and Rockwell 2013). In addition, Burrowing Owl (*Athene cunicularia*) nest site density and number of young fledged decreases in residential areas of Florida where development exceeds 60% (Millsap and Bear 2000). Similar relationships may exist in which levels of noise or light pollution reach an intensity causing owls to avoid areas of otherwise suitable habitat. Identification of such relationships could provide important information to better manage the configuration of developing landscapes to allow owls to persist.

In this study, our objective was to identify factors influencing Great Horned Owl population density at multiple spatial scales in a preserved area within a rapidly urbanizing landscape. We combined our acoustic datasets collected over two sampling years with high-resolution data on anthropogenic noise, artificial light, and landcover to examine the relationships among these variables and estimated density of Great Horned Owls in the Chattahoochee River National Recreation Area, Georgia using generalized linear models (GLMs). Modeling owl density in response to landscape factors at multiple spatial scales allows us to identify the occurrence of specific interactions that may be overlooked with a single-scale approach. Our understanding of how individuals' responses to their environment varies with spatial scale is essential to determine where management applications would be most effective.

In accordance with past studies of other owl species, we expected to find a threshold of urban intensity at which Great Horned Owl density begins to decline in our study area. Specifically, we hypothesized that variables related to landscape heterogeneity would be positively associated with Great Horned Owl density, due to their preference for edge habitat, but we would see an inverse relationship develop due to increasing levels of anthropogenic noise and light present along edges of the study area in closest proximity to human development (Artuso et al. 2013). Further, we expected the effects of urbanization to vary at different spatial scales as observed in similar studies (e.g., Pagaldai et al. 2021), but to be most evident at the local and home range scale.

Methods

Study Area

This study took place in the Chattahoochee River National Recreation Area (CRNRA), a 4,000-ha park extending 48 miles along the Chattahoochee River between the city of Atlanta, Georgia to the south and Lake Lanier to the north. Land cover here includes uplands with mixed pine and hardwood communities composed of predominantly tulip-poplar (*Liriodendron tulipifera*), American beech (*Fagus grandiflora*), oak (*Quercus spp.*), loblolly pine (*Pinus taeda*), and shortleaf pine (*Pinus echinata*) as well as lowland floodplains and riparian areas dominated by canopy species, such as river birch (*Betula nigra*) and green ash (*Fraxinus pennsylvanica*) (Byrne et al. 2014). Much of the area surrounding the park has high intensity urban land cover (i.e., central business districts, multi-family dwellings, commercial, industrial, and institutional facilities with high percentages of impervious surface area) especially where the river nears Atlanta (Figure 1.1).

Acoustic data

Two acoustic datasets collected within an acoustic spatial capture-recapture framework between 2020 and 2021 were used to estimate the population density of Great Horned Owls in the CRNRA (see Chapter 2 for additional details). Sampling was conducted using autonomous recording units (SM2, SM2+, SM3; Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) programmed to record on alternate nights during the spring breeding season when owls are most vocally active. Sampling sites were primarily selected at random within areas identified as suitable habitat for Great Horned Owls. Additional steps were taken to ensure sampling occurred along a development gradient based on percent impervious cover (NLCD 2019; Dewitz 2021), allowing us to sample the range of anthropogenic noise and artificial light levels in the study area.

Anthropogenic variables

Anthropogenic noise data was obtained through the National Park Service Data Store (2013-2015). The data consists of georeferenced maps of expected environmental sound levels across the contiguous United States generated by machine learning models. The models also produced estimated natural sound levels by minimizing anthropogenic inputs, which were then subtracted from the existing sound levels to obtain estimated 'impact' sound levels. The impact level includes sound produced only by anthropogenic sources; therefore, we used the A-weighted L_{50} anthropogenic sound pressure level at 270 m resolution as our measure of noise pollution in the study area (Buxton et al. 2017, Senzaki et al. 2020). Although noise levels were estimated for a summer daytime hour (7AM-7PM) and our acoustic surveys occurred at night, we can assume the data is still applicable, because Great Horned Owls most often vocalize from the immediate nest vicinity. Therefore, we likely detected them in the same areas they inhabit throughout the day during the breeding season (Artuso et al. 2013).

We obtained data from the world atlas of artificial sky luminance depicting simulated zenith radiance from anthropogenic sources ($\mu cd/m^2$) at 270 m resolution. The atlas was produced through high-resolution measurements of upward radiance acquired from six months of satellite data by the Light Pollution Science and Technology Institute (Falchi et al. 2016). To separate the effects of noise and light pollution from other indices of urban intensity, we also obtained data on human population density at the block level from the 2010 U.S. Census (U.S. Census Bureau 2010), which was converted to a raster dataset with 270 m resolution.

Landscape variables

We selected a set of variables describing landscape patterns we expected to be important predictors of Great Horned Owl density based on our review of the literature (Fuller 1979, Petersen 1979, McGarigal and Fraser 1984, Morrell and Yahner 1994, Artuso et al. 2013). The selected composition and configuration metrics include: (1) percent forest cover (PFC), (2) percent developed cover (PDC), (3) forest edge density (ED), (4) area-weighted mean forest patch size (MPS), (5) forested landscape shape index (LSI), and (6) Shannon's diversity index (SHDI). Percent forest and percent developed cover are the sum of all areas of each patch type (m^2) divided by the total area of the landscape (m^2) converted to a percentage. Edge density (m/ha) is the total length of forest edge divided by the total landscape area. The area-weighted mean patch size describes the average area (ha) of forest patches considering the size distribution of patches within the area of interest. Landscape shape index is a function of the sum of all forest edge segments and the total landscape area that describes the complexity of patch shapes, with an LSI of 1 indicating the lowest complexity. Shannon's diversity index accounts for the number of patch types and the abundance of each type to describe the heterogeneity of the landscape, with an SHDI of 0 indicating no diversity (McGarigal and Marks 1995).

Analysis of predictor variables

We used 30 m resolution land cover data from the 2019 National Landcover Dataset to assess our landscape metrics of interest (Dewitz 2021). The land cover data were reclassified to two binary layers in ArcMap 10.6.1 (ESRI 2018): one with forest (i.e., values 41-43) and non-forest classes and one with developed (i.e., values 21-24) and undeveloped classes. To investigate how landscape variables affect Great Horned Owl density at multiple scales, we calculated metrics at the site scale (13 ha), home range scale (250 ha), and landscape scale

(10,000 ha) by conducting moving window analyses with an eight-cell rule in Fragstats version 4.2 (McGarigal et al. 2012). The site scale corresponds to the effective sampling area of an ARU estimated by the acoustic SCR model. The home range scale was selected based on estimates reported in other regions of the U.S., and the selected landscape scale follows the methods of previous raptor studies that identified responses at this scale (Martínez and Zuberogoitia 2004a, 2004b, Artuso et al. 2013). Anthropogenic variables of noise, light, and human population density were also analyzed at the home range and landscape scale. To quantify these variables at the site scale, we used single pixel extraction as the pixel size (270 m) was the highest resolution available and corresponded to the site scale.

All variables were screened for collinearity using Pearson's correlation matrices prior to inclusion in models of Great Horned Owl density. We defined variables with strong correlations considering a threshold $|r| = 0.60$ and did not include these variables within the same model (Green 1979). All continuous variables were scaled using model functions in R prior to analysis to enable direct comparisons of effects.

Model development

Owl density was modeled using generalized linear models within the *ascr* package in R version 4.0.2 (R Core Team 2020). We ran 20 candidate models at each scale followed by a fourth set of 20 models combining variables at different scales. Within model sets, we considered a null model, global models with all covariates, and models fitted for all possible combinations of covariates including potential interactions and quadratic effects. All models included a random effect of 'year' as our acoustic dataset was pooled across both surveys. We ranked models using Akaike's Information Criteria for small sample sizes (AIC_c) and selected those with a $\Delta AIC_c < 2$ for making model-averaged predictions as recommended when the weight of the top model is less than 0.9 (Burnham and Anderson 2002, Grueber et al. 2011). To estimate model-averaged parameters, we used the zero method to avoid inflation of beta coefficients, as recommended when comparing effect sizes among variables of interest (Burnham and Anderson 2002, Nakagawa and Freckleton 2010).

Results

Great Horned Owl density in the CRNRA was best predicted by a model including site level covariates of noise, human population density, percent forest cover, and edge density (Table 3.2). Three additional models within 2 ΔAIC_c of the top-ranking model also included covariates of light at the site scale and human population density at the landscape scale. Estimated coefficients of the top models indicate forest cover and edge density have a positive effect on owl density, while covariates of noise, light, and human density appear to have a negative effect (Table 3.3a). Each of the top-ranking models included covariates of noise, forest cover, and edge density, which all appear to be most important at the site-scale. Interactions between variables did not improve model AIC. Landscape variables of area-weighted mean patch size, landscape shape index, and percent developed cover were not included in any competitive models of owl density. The null model including only the variable of year was the lowest ranked model out of all considered.

We used the top four models to make model-averaged predictions of Great Horned Owl density. Of the variables mentioned, forest cover, edge density, and noise were significantly correlated with owl density, with noise having a stronger effect on the response variable (Table 3.3b). Model-averaged predictions indicate Great Horned Owl density in the CRNRA increases with forest cover and forest edge density (Figures 3.1-2) and decreases with noise intensity, nearing an estimated 0 individuals per hectare where noise exceeds 15 dB (Figure 3.3). These effects are illustrated in our predicted density surfaces for the entire study area (Figures 3.4-11). Estimated owl density is predicted to be lowest in areas where noise levels are highest, which was strongly correlated with urban intensity (i.e., percent developed cover, refer to Figure 1.1).

Discussion

We found evidence of a negative relationship between anthropogenic noise and Great Horned Owl density in the CRNRA. This finding is consistent with previous studies that identified negative effects of noise on owl occupancy, but it is the first to describe population density in response to noise. We did not identify a “threshold” of urban intensity as we originally expected; instead, we found a gradual decline in owl density with increasing noise intensity that reached zero at the highest noise levels we sampled. This result was unexpected, because past research has shown owls can tolerate some level of human development. It may be an indication that anthropogenic noise levels in the study area are already above an intensity which interferes with hunting success, vocal communication, and other natural behaviors. Only one other study to our knowledge has investigated the effect of noise on Great Horned Owls by assessing occupancy in forested areas near industrial noise sources, and no significant relationship was observed with only minimal differences in occupancy between sites with and without chronic noise (Shonfield and Bayne 2017). Our contrasting results may be due in part to the response variables that were measured. Because population density provides more information on population status than occupancy, it may have allowed us greater insight into how Great Horned Owls respond to their environment.

The positive relationship between owl density and forest edge habitat supports our hypothesis that Great Horned Owls would show preference for areas with greater heterogeneity as previous studies have demonstrated (e.g., Grossman et al. 2008). Interestingly, we did not identify a significant interaction between edge density and noise, which we had expected, because edges are exposed to higher noise levels than interior forest. Our models indicate the negative effect of noise on owl density is stronger than the positive effect of edge density. The likelihood of greater prey availability along edges is most likely driving this positive effect. Much of the forest edge in our study area is created by the Chattahoochee River, a major water source that would be attractive to prey and Great Horned Owls as a result.

Percent developed cover was not included in any competitive models of Great Horned Owl density, which is consistent with findings from studies of other urban-adapted raptors (e.g., Barred Owl, Clément et al. 2019, 2021). Developed cover was correlated with noise at multiple scales, so these variables were not included in the same models, and models which included developed cover in place of noise did not improve AIC. Similarly, landscape shape index was not an important predictor relative to edge density, to which it was highly correlated. Percent forest cover was an important predictor in all of the top models with several indicating a significant effect on owl density. A positive association with forest cover is supported by previous work investigating Great Horned Owl’s response to landscape composition (Grossman et al. 2008). The amount of forest cover available appears to be of greater importance than average forest patch size, as this variable was not included in our top models and was highly correlated with percent forest cover. Notably, Shannon’s Diversity Index was included in a model with a difference of just 2.09 AIC_c from the top model, indicating the importance of landscape heterogeneity in positively influencing owl density.

We did not identify a significant relationship between light pollution and the density of owls in the CRNRA. However, light pollution at the local scale did explain more variation in owl density than other non-significant variables included in the top model set (i.e., human population density; Figure 3.3b). Although Great Horned Owls do not appear to be affected by artificial light levels compared to other urbanization by-products, this may not be the case for other raptors. Contrasting effects of light have been reported for different owl species, some of which appear to benefit from greater insect availability near light sources (e.g., Burrowing Owl, *Athene cunicularia*, Rodríguez et al. 2021), while others avoid areas of greater light intensity (e.g., Mottled Owl, *Ciccaba virgata*, Marín-Gómez et al. 2020).

The most important landscape and anthropogenic variables describing Great Horned Owl density appear to be operating at the local scale, which we considered to be within 13 ha of our study sites (i.e., the effective sampling area). It is worth noting that noise measured at the home range scale was included in a model within 4.93 ΔAIC_c of the top-ranking model, indicating its importance to a lesser degree. Although our results indicate low owl density where noise levels are high, we cannot conclude from this study that anthropogenic noise leads to poor quality habitat for Great Horned Owls. More research is needed to assess demographic parameters in areas of varying noise exposure to determine if there is any effect on owl fitness. Although such fine-scale studies are more challenging, they are necessary before any management plans are considered. Great Horned Owls are not currently indicated to be in decline in any part of their range, but populations should be studied in more detail to understand their response to landscapes undergoing rapid change.

Conclusion

We identified several important landscape and anthropogenic factors influencing Great Horned Owl density in the CRNRA. In doing so, we have added to the growing body of evidence that suggests owls are negatively impacted by anthropogenic noise. However, further research is needed to determine whether noise actually decreases the quality of habitat by altering owl fitness. For existing monitoring programs in areas of conservation concern, our use of autonomous recording units to assess population status could easily be incorporated to increase understanding of species' responses to urban stressors. Protected areas, such as the CRNRA, may provide opportune locations to initiate monitoring efforts where noise management policies could more feasibly be implemented if conservation needs exist. Populations of Great Horned Owls in habitats with heavy noise exposure may be in particular need of assessment over time as urban expansion continues.

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Table 3.1. Description of landscape and anthropogenic metrics used to develop models of great horned owl density in the CRNRA.

Variable	**Description**	**Unit**	**Data Source**
pfc200	Proportion of forested cover within 13 ha	%	Dewitz 2021
pfc900	Proportion of forested cover within 250 ha	%	Dewitz 2021
pfc5640	Proportion of forested cover within 10,000 ha	%	Dewitz 2021
pdc200	Proportion of developed cover within 13 ha	%	Dewitz 2021
pdc900	Proportion of developed cover within 250 ha	%	Dewitz 2021
pdc5640	Proportion of developed cover within 10,000 ha	%	Dewitz 2021
mps200	Area-weighted mean patch size of forest within 13 ha	ha	Dewitz 2021
mps900	Area-weighted mean patch size of forest within 250 ha	ha	Dewitz 2021
mps5640	Area weighted mean patch size of forest within 10,000 ha	ha	Dewitz 2021
ed200	Edge density within 13 ha	m/ha	Dewitz 2021
ed900	Edge density within 250 ha	m/ha	Dewitz 2021
ed5640	Edge density within 10,000 ha	m/ha	Dewitz 2021
lsi200	Landscape shape index of forest within 13 ha	Index	Dewitz 2021
lsi900	Landscape shape index of forest within 250 ha	Index	Dewitz 2021
lsi5640	Landscape shape index of forest within 10,000 ha	Index	Dewitz 2021
shdi200	Shannon’s diversity index within 13 ha	Index	Dewitz 2021
shdi900	Shannon’s diversity index within 250 ha	Index	Dewitz 2021
shdi5640	Shannon’s diversity index within 10,000 ha	Index	Dewitz 2021
noise	A-weighted L_{50} anthropogenic sound pressure level at 270 m resolution	dB	NPS Data Store
noise900	A-weighted L_{50} anthropogenic sound pressure level within 250 ha	dB	NPS Data Store
noise5640	A-weighted L_{50} anthropogenic sound pressure level within 10,000 ha	dB	NPS Data Store
light	Zenith radiance from anthropogenic sources at 270 m resolution	$\mu cd/m^2$	Falchi et al. 2016
light900	Zenith radiance from anthropogenic sources within 250 ha	$\mu cd/m^2$	Falchi et al. 2016
light5640	Zenith radiance from anthropogenic sources within 10,000 ha	$\mu cd/m^2$	Falchi et al. 2016
human	human population density at the block level	#/block	U.S. Census Bureau
human900	human population density within 250 ha	#/block	U.S. Census Bureau
human5640	human population density within 10,000 ha	#/block	U.S. Census Bureau

Scales: Site = 200 m radius; Home Range = 900 m radius; Landscape = 5640 m radius

Table 3.2. Candidate models explaining the density of great horned owls in the CRNRA. Akaike's information criterion (AIC_c), the difference between the given model and the model with lowest AIC (ΔAICc), the number of parameters (K), and the Akaike weight are reported for each model. See Table 3.1 for descriptions of variables.

Model	**K**	**AICc**	**ΔAICc**	**w**
D(year + noise + human + pfc200 + ed200)	9	7929.12	0.00	0.24
D(year + noise + pfc200 + ed200)	8	7929.21	0.09	0.23
D(year + noise + human5640 + pfc200 + ed200)	9	7929.56	0.44	0.19
D(year + noise + light + pfc200 + ed200)	9	7931.03	1.91	0.09
D(year + noise + pfc200 + ed200 + shdi200)	9	7931.21	2.09	0.08
D(year + noise*human + pfc200 + ed200)	10	7932.43	3.31	0.05
D(year + noise + light + human + pfc200 + ed200 + shdi200)	11	7932.87	3.75	0.04
D(year + noise + ed200)	7	7933.30	4.18	0.03
D(year + noise900 + light + human + pfc200 + ed200)	10	7934.04	4.93	0.02
D(year + noise900 + human + pfc200 + ed200 + shdi200)	10	7934.59	5.47	0.02
D(year + noise + light + ed200)	8	7935.01	5.89	0.01
D(year + noise900 + light + pfc200 + ed200 + shdi200)	10	7935.28	6.16	0.01
D(year + noise5640 + pfc200 + ed200)	8	7936.17	7.06	0.01
D(year + human5640 + pfc200 + ed200)	8	7939.99	10.87	<0.01
D(year)*	5	7974.17	45.05	<0.01

*Null model

Table 3.3a. Standardized parameter estimates from each of the four best models of Great Horned Owl density with standard errors (SE), 95% confidence intervals (CI), and significance values (P). Refer to Table 3.2 for full model descriptions.

Model	β	Estimate	SE	95% CI	P
1	noise	-0.719	0.161	(-1.035, -0.403)	8.16 x 10^{-6}
	ed200	0.010	0.002	(0.006, 0.015)	2.61 x 10^{-6}
	pfc200	0.013	0.007	(-4.18 x 10^{-4}, 0.026)	0.058
	human	-2.79 x 10^{-4}	0.001	(-6.60 x 10^{-4}, 1.03 x 10^{-4})	0.152
2	noise	-0.688	0.159	(-1.001, -0.376)	1.54 x 10^{-5}
	ed200	0.010	0.002	(0.006, 0.014)	1.87 x 10^{-6}
	pfc200	0.016	0.007	(0.003, 0.028)	0.016
3	noise	-0.603	0.171	(-0.938, -0.268)	4.22 x 10^{-4}
	ed200	0.010	0.002	(0.006, 0.014)	5.85 x 10^{-6}
	pfc200	0.014	0.007	(0.002, 0.027)	0.029
	human5640	-0.001	0.001	(-0.003, 0.001)	0.201
4	noise	-0.609	0.245	(-1.090, -0.128)	0.013
	ed200	0.010	0.002	(0.006, 0.014)	1.97 x 10^{-6}
	pfc200	0.017	0.007	(0.003, 0.031)	0.018
	light	-0.070	0.166	(-0.395, 0.256)	0.675

Table 3.3b. Model-averaged parameter estimates (β) from the top model set (< 2 ΔAICc), with standard errors (SE), and 95% confidence intervals (CI).

β	Estimate	SE	95% CI
Intercept	0.856	2.242	(0.011, 69.320)
ed200	0.010	0.002	(0.006, 0.014)
noise	-0.666	0.173	(-1.006, -0.327)
pfc200	0.015	0.007	(0.002, 0.028)
light	0.015	0.007	(-0.048, 0.031)
human	-8.88 x 10^{-5}	6.19 x 10^{-5}	(-2.10 x 10^{-4}, 3.26 x 10^{-5})
human5640	-3.29 x 10^{-4}	2.57 x 10^{-4}	(-0.001, 1.75 x 10^{-4})

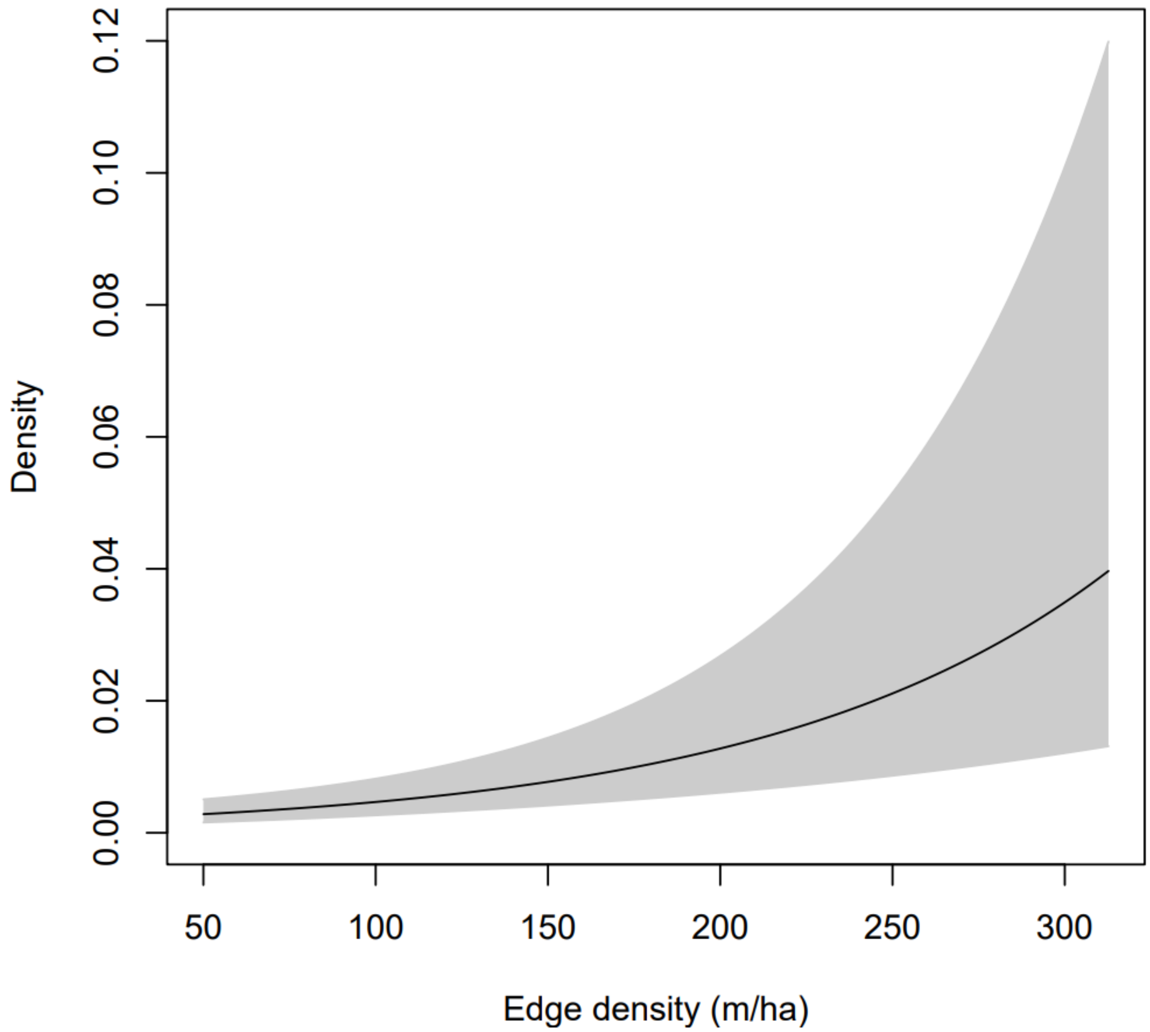

Figure 3.1. Model-averaged predicted Great Horned Owl density as a function of edge density (m/ha) in the CRNRA.

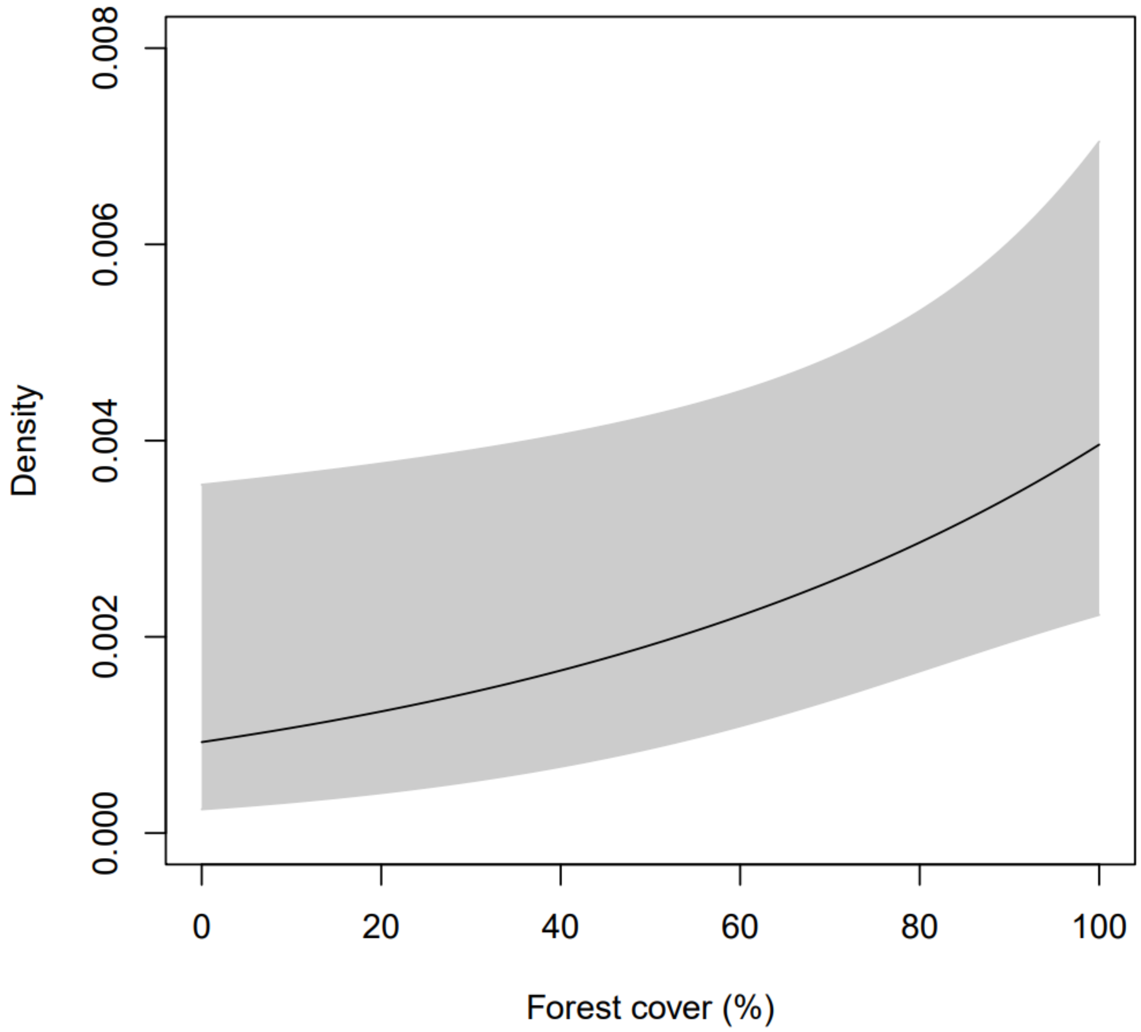

Figure 3.2. Model-averaged predicted Great Horned Owl density as a function of percent forest cover in the CRNRA.

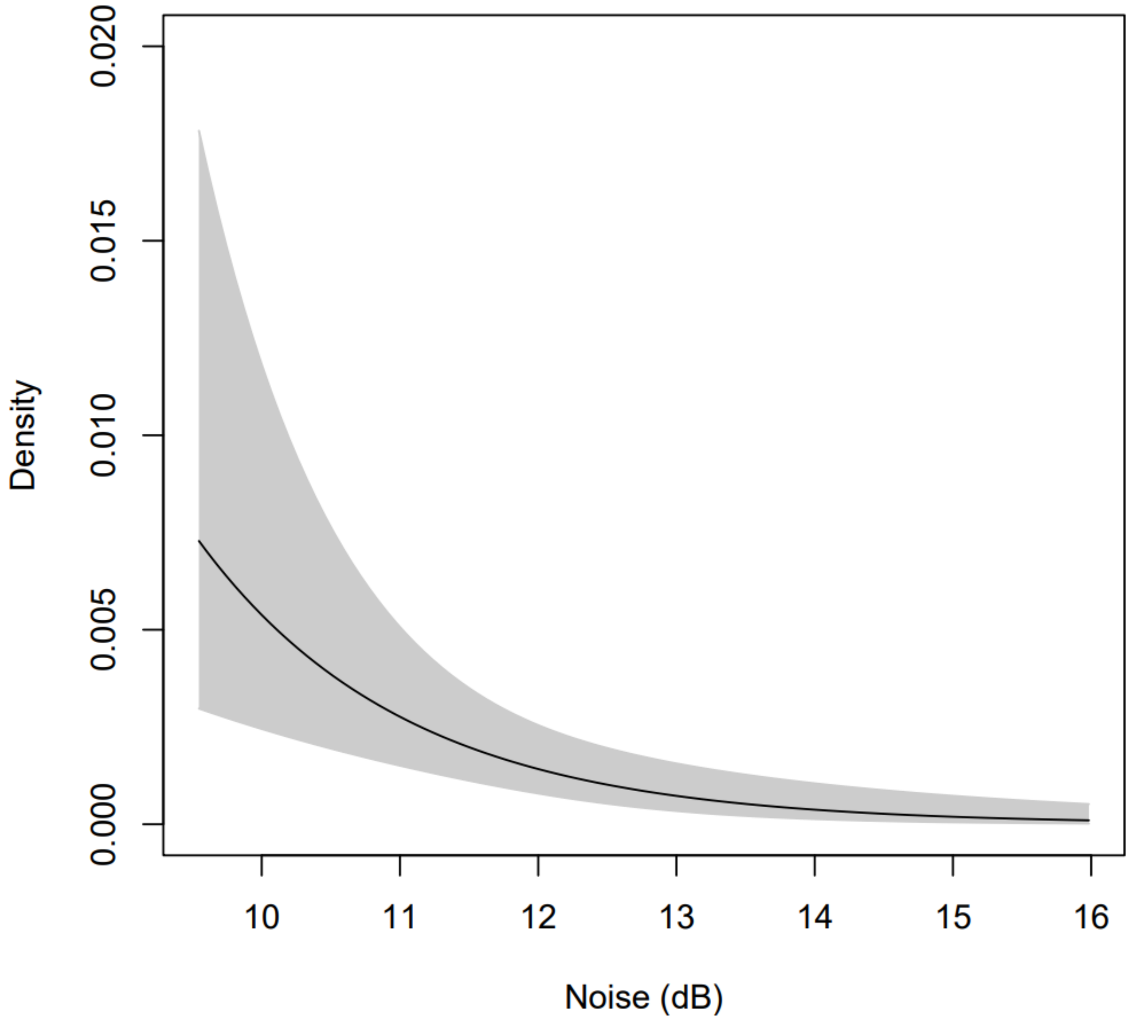

Figure 3.3. Model-averaged predicted Great Horned Owl density as a function of anthropogenic noise intensity (dB) in the CRNRA. Our measure of anthropogenic noise is the impact level (i.e., difference between natural and existing sound levels).

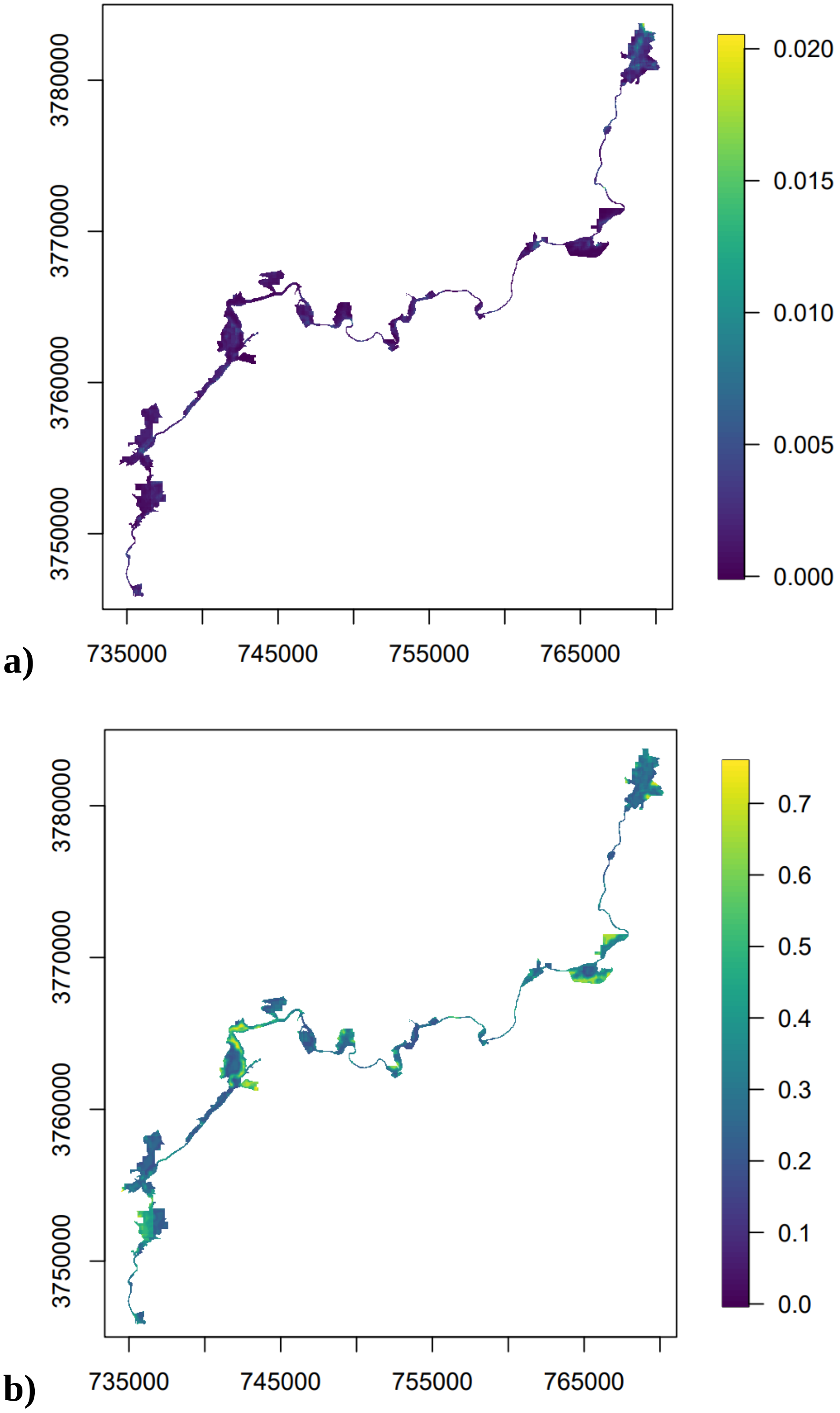

Figure 3.4. Predicted a) Great Horned Owl density (individuals/ha) in 2020 and b) coefficient of variation from the top-ranked model.

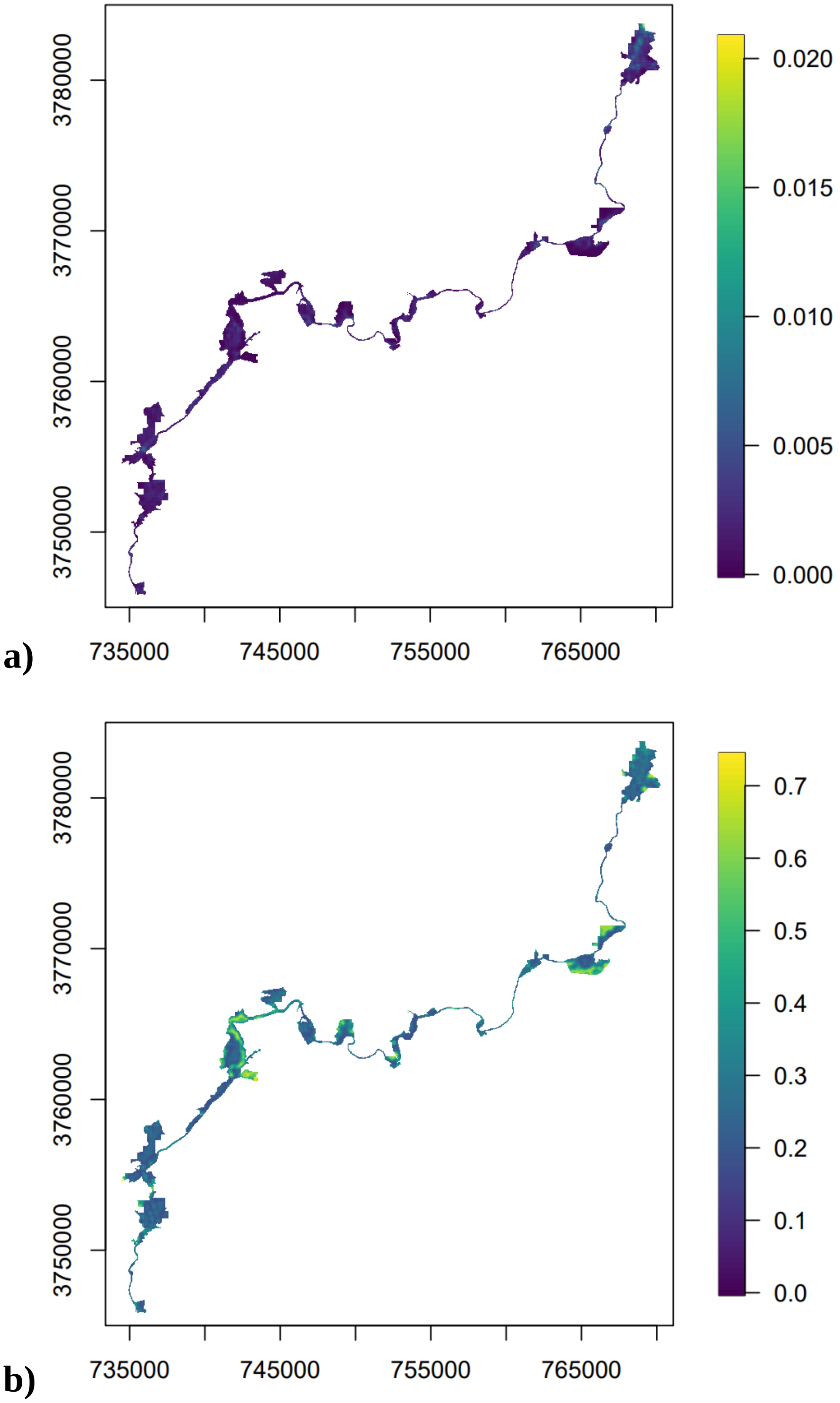

Figure 3.5. Predicted a) Great Horned Owl density (individuals/ha) in 2020 and b) coefficient of variation from the second-ranked model.

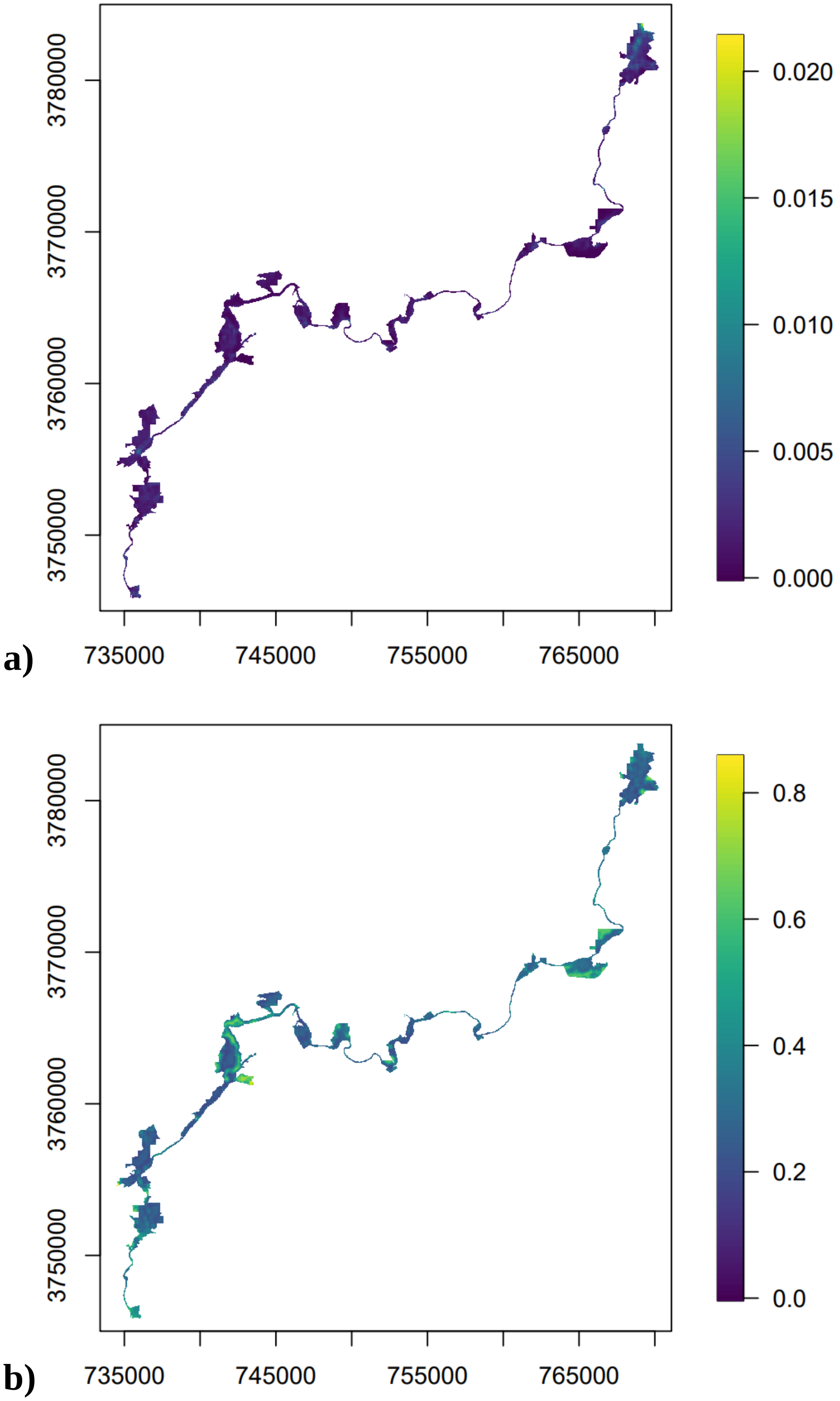

Figure 3.6. Predicted a) Great Horned Owl density (individuals/ha) in 2020 and b) coefficient of variation from the third-ranked model.

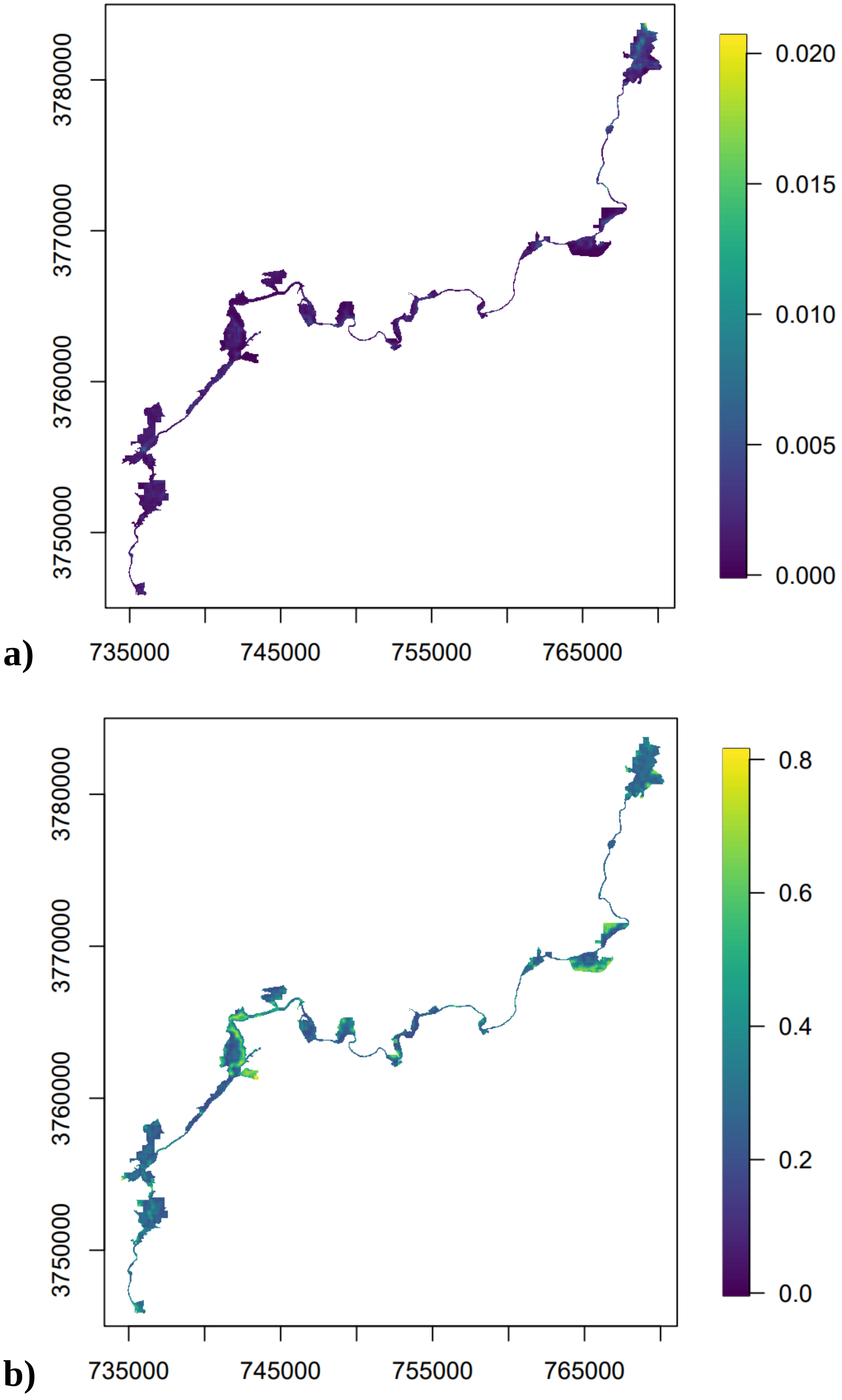

Figure 3.7. Predicted a) Great Horned Owl density (individuals/ha) in 2020 and b) coefficient of variation from the fourth-ranked model.

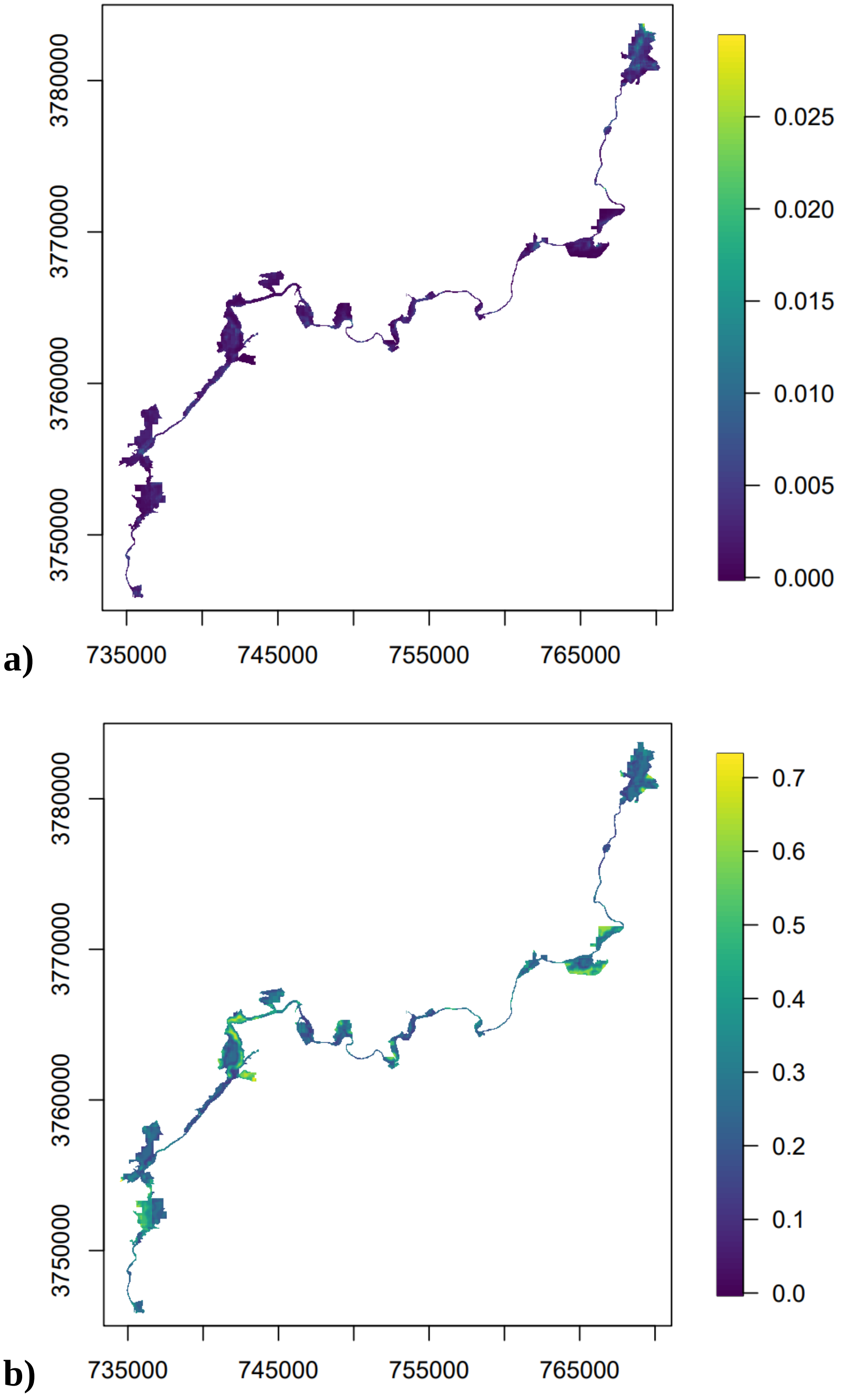

Figure 3.8. Predicted a) Great Horned Owl density (individuals/ha) in 2021 and b) coefficient of variation from the top-ranked model.

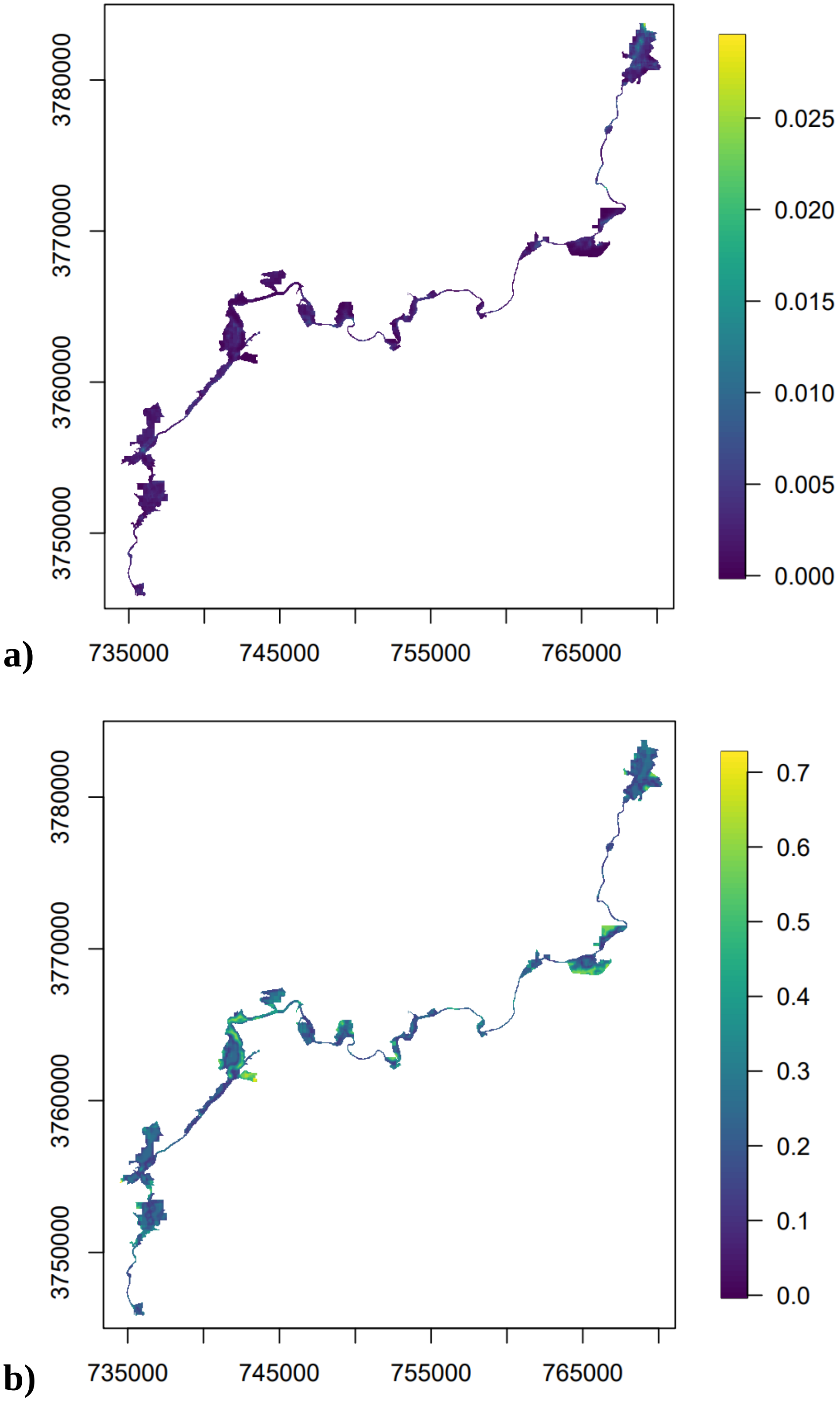

Figure 3.9. Predicted a) Great Horned Owl density (individuals/ha) in 2021 and b) coefficient of variation from the second-ranked model.

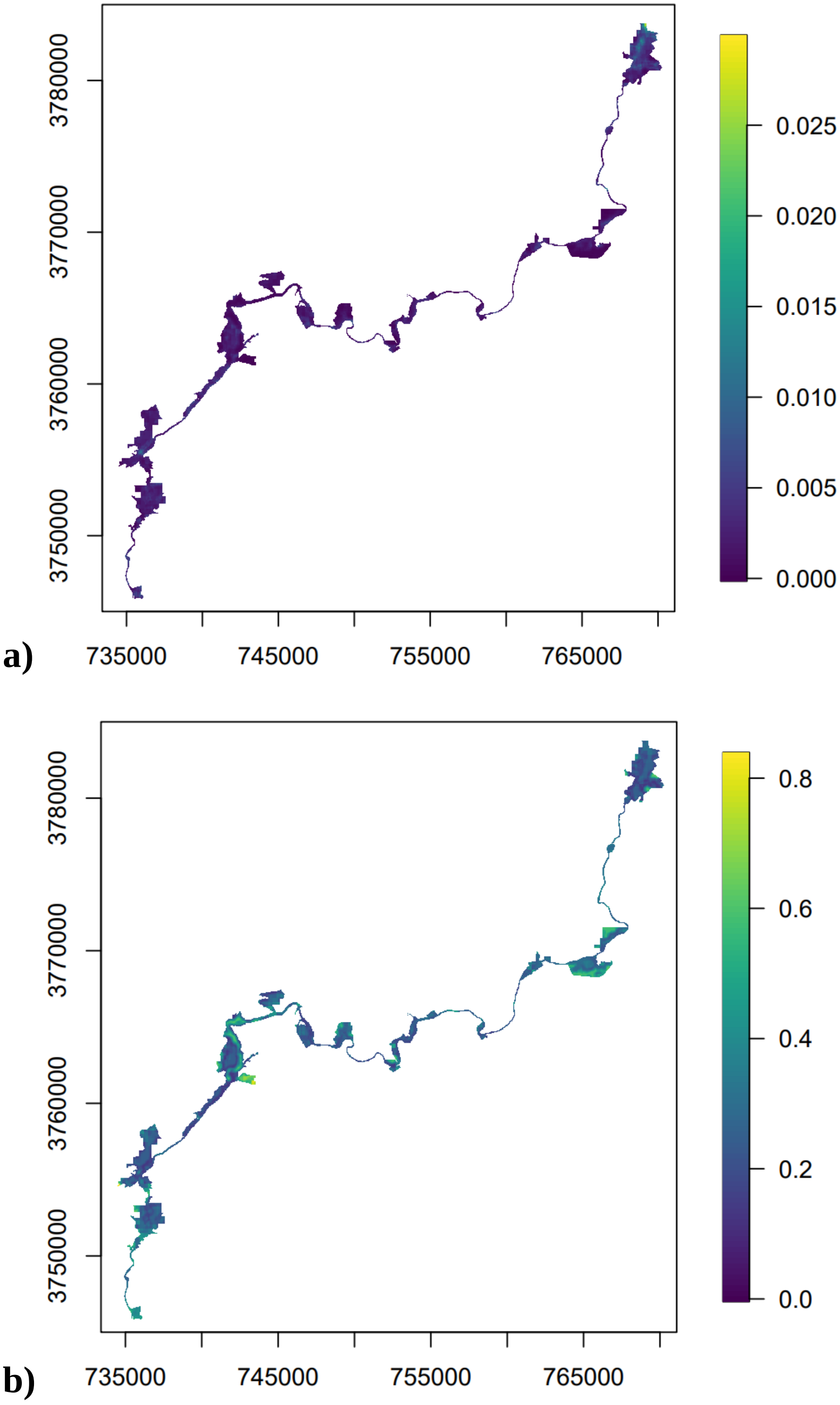

Figure 3.10. Predicted a) Great Horned Owl density (individuals/ha) in 2021 and b) coefficient of variation from the third-ranked model.

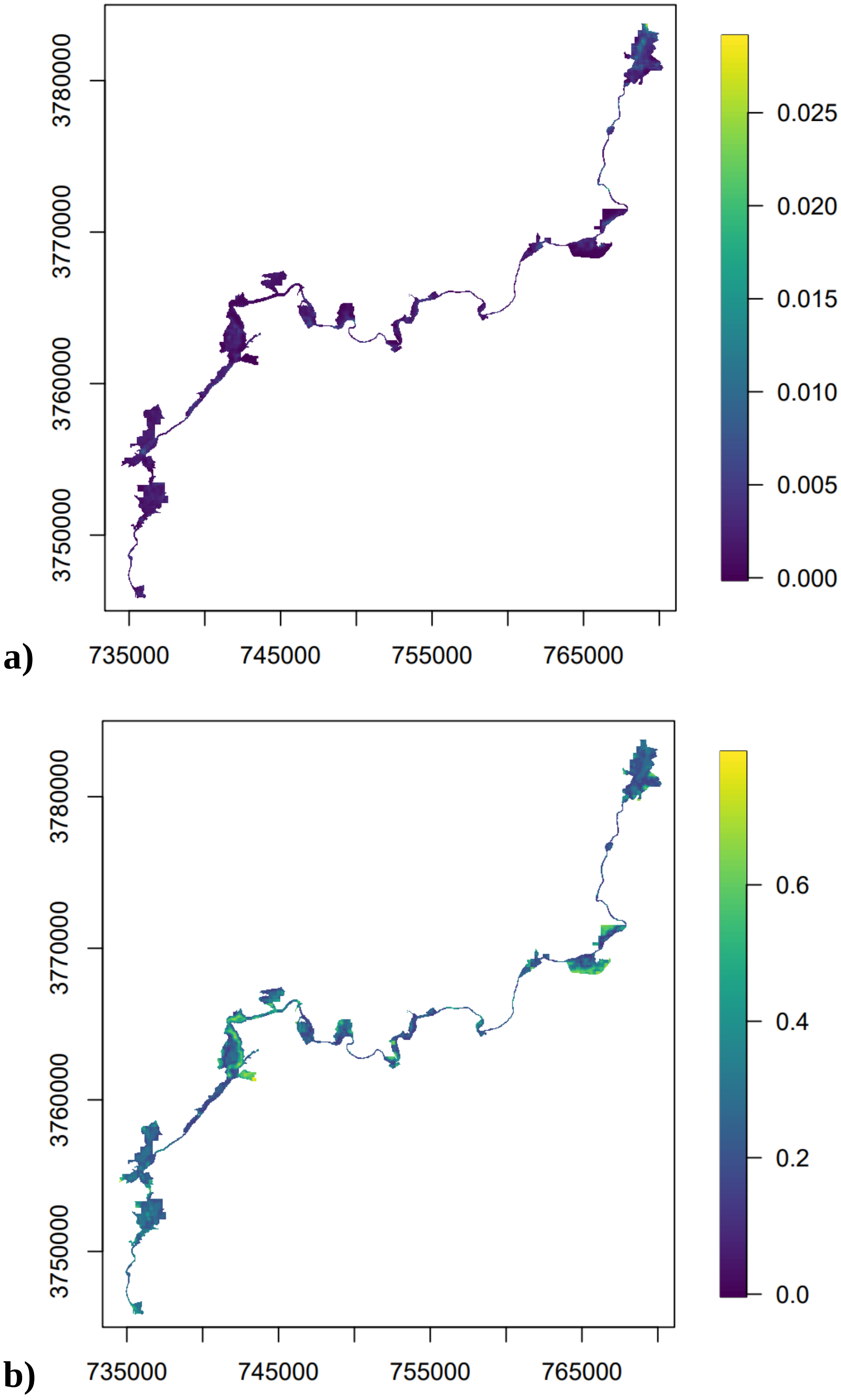

Figure 3.11. Predicted a) Great Horned Owl density (individuals/ha) in 2021 and b) coefficient of variation from the fourth-ranked model.

CHAPTER 4

SUMMARY AND CONCLUSIONS

Summary and conclusions

The primary objectives of this study were to: 1) explore whether acoustic spatial capture-recapture (SCR) could be used to reliably estimate population density of owls and 2) investigate the influence of anthropogenic factors of noise and light pollution on owl density in the Chattahoochee River National Recreation Area (CRNRA). Acoustic SCR has been used to estimate population density of various taxa, including one avian species, and we expected it to be equally effective in estimating populations of owls. Traditional surveys, such as the North American Breeding Bird Survey, are unsuited for detecting owls due to their elusive, nocturnal behavior; therefore, few population estimates are available for most species. In addition, little is known on the impact of anthropogenic factors on the population density of owls within highly urbanized areas. Some studies point to evidence of reduced occupancy and hunting success with increasing noise levels, while others suggest minimal effects. Because owls can tolerate—and exploit—some levels of human development, we hypothesized a threshold of urban intensity to exist at which we would see sharp declines in owl density due to the potential effects from noise and light pollution.

In chapter two, we estimated the population density of Great Horned Owls in the CRNRA using acoustic SCR models. We evaluated the validity of our chosen methods for acoustic discrimination and found no indication of misclassification. These methods were not reliable for discriminating individual Barred Owls, so we used acoustic SCR to estimate call density opposed to animal density. The same decision was made for Eastern Screech-Owls due to an insufficient number of call detections over both survey years. Overall, our findings support our hypothesis that acoustic SCR is a useful technique for monitoring owl populations. We were able to provide the first estimate of population density for an owl species using acoustic data. In doing so, we also avoided a major limitation of traditional survey techniques: acoustic surveys were well suited to detect owls as they could be conducted at night during the breeding season when owls are most vocally active. They were also noninvasive; we did not physically capture individuals or attempt to attract them to areas they may not normally be. Moreover, acoustic surveys required less field effort and personnel. Our study further illuminates the utility of acoustic SCR for monitoring elusive species that vocalize and can be distinguished by their calls.

Additional research is still needed to improve the use of acoustic SCR for estimating owl populations. The success of this method is highly dependent upon the ability to assign identities to calling individuals, which requires species to possess individually distinct vocalizations. We did not find SPCC and hierarchical clustering methods suitable for individual discrimination of Barred Owls, but we focused on only one call type determined individually distinctive in previous studies. Further investigation of vocal individuality in Barred Owls may discern calls possessing more individually distinct characteristics that can be discriminated using SPCC similar to Great Horned Owls in our study. In addition, there is currently no consensus on which method of acoustic discrimination is best, and it may be that another method would prove more useful for Barred Owls. Another option for future studies of Barred Owls is to obtain an independently estimated call rate for the population under study to alleviate the need to identify individuals. Call density can be converted to animal density when call rate is known, but this option adds an extensive fieldwork burden to acoustic surveys.

In this study, we were limited in our ability to obtain time-of-arrival data due to the size of our sampling arrays, and this likely affected precision of our density estimates. We expected data on measured signal strengths to provide enough information to improve inference on animal locations, consistent with previous studies. Instead, we added further support to findings that signal strengths offer little in the way of increasing estimator precision. Another limitation in our study was low capture success for Eastern Screech-Owls, which rendered us unable to reliably estimate population density. We cannot conclude whether acoustic SCR is useful for monitoring populations of screech-owls, but our findings indicate future studies may have better success using call broadcast surveys to assess presence in areas of interest before conducting large-scale studies with ARUs. If a sufficient number of detections can be obtained this way, it is likely population density could be estimated using acoustic SCR, as previous studies have shown individual screech-owls can be discriminated with model-based clustering.

In chapter three, we conducted a multi-scale analysis of factors influencing Great Horned Owl density in the CRNRA by pairing our acoustic dataset collected over two breeding seasons with high resolution noise, light, and landcover data. We developed a set of competitive models using Akaike's Information Criterion and assessed the relative importance of predictor variables. Our results supported our hypotheses that Great Horned Owls are positively associated with landscape heterogeneity and negative associated with anthropogenic noise. However, we did not find a significant relationship between light pollution and owl density as we had originally predicted. In this study, we have added to the growing body of evidence that anthropogenic noise has negative effects on birds and owls in particular.

Future studies investigating the effects of noise on species of interest may benefit from abundance or density estimation opposed to occupancy. We suggest this may have allowed us identify a significant effect of noise on Great Horned Owls when similar studies did not. For studies employing acoustic SCR to estimate population density, we emphasize the need to obtain time-of-arrival data on call detections to increase model precision. It is likely this additional information would have helped us avoid presenting large confidence intervals with our model predictions, which are less informative. Further, we encourage a multi-scale approach to model selection to ensure processes occurring at specific scales are not overlooked. By identifying the scale of effect, we can apply management strategies where they will be most effective.